Transcript

Conversation Between Trish Uhl and Julie Stone

Julie: So Trish, I just want to say thank you for spending a little extra time with me today. For those of you who were with us earlier today, you know that Trish was here joining Fredrickson Learning to present on how we advance learning and performance using AI and data analytics.

Trish: Mm-hm. Thanks, Julie. I'm super excited. I'm really glad that we're having this conversation.

Julie: I am too. As you were talking, first of all, just to provide the overview of the landscape of where technology is today, there were a lot of things that jumped to mind for me. You were talking about a number of technologies that are already here today that we're going to start to see in force in 2020 across all facets of our lives. And what started going through my head is, certainly within the field of learning, but in others as well, technology doesn't always trickle down as fast as we experience it in other aspects of our lives.

And so, from a readiness perspective, if we as learning leaders want to start figuring out how do we get our [organizations] on this journey to evolve and start to use data that will help us drive improved performance and start to use AI, how do we get ready for that and are there critical readiness factors that need to be in place before we can get started?

Trish: Yeah, it's a big challenge, and common around the world with learning leaders and trying to be able to advance the organization forward. And really step up into a partnership, right, and into a leadership position and helping lead the organization into this new arena.

So how do we do that? Part of it is, one of the biggest challenges we have with people, and we know this from change management and from trying to change any kind of behavior or culture in any kind of context, and that is: human beings are really wired for concrete, firm examples. Things we can touch and feel and experience with any of our five senses. We struggle, and we know this from a lot of the psychological and the sociological research, that we really struggle with abstract things that are on these fuzzy time horizons that are somewhere that seem off in the distance. But the things that are immediate and the things that again we can sense and feel and touch and listen to and really have that experience of that are more immediate.

And so, the first thing we need to do for our organization, for our front line, for our managers, for our executive team, when it is that we're leading this forward is to help bring this home, right, is to provide examples and experiences that helps people connect with what's actually happening and why there's some level of urgency around it. And the best way to do that is to create a condition that allows people to have that kind of experience so that they kind of discover on their own.

So the way to facilitate that might be, as an example, for some organizations, it's to take people on a field trip to another organization that's farther ahead doing something that you have vision for that you want to help move your organization, your team, leadership, in that particular direction. Well then give them the benefit of an experience of seeing somebody else in the market or a competitor or somebody in another domain that would be relevant; that would help them have it in context. To have the experience and see whatever that is in action.

The other one is, it's like, kind of what it is I was trying to orchestrate in the room today where we did a lot of examples that really talked about, to your point, our consumer lives, our lives at home, how it is that we're using these new devices like the Ring security device or the Nest thermostat. And then I was talking about how we travel now, like often times, I think most likely when we go into airports and we see the "Happy or Not" buttons now, especially around the washrooms and those types of things. So how do we take something that's abstract, that doesn't feel like its immediately on fire like every other priority in our work lives is, and how do we help bring it home to people that this is happening and needs attention. We can only do that by providing the experience to them and we can do that by making it real. And those are a couple of the different ways that we can go ahead and facilitate that.

Julie: Yeah, so what I'm thinking is in order to make it real and also make it something that people care about, it's got to be something that they're trying to solve. That the organization is trying to solve. Either the methods they're using aren't working or they're not happening fast enough, which I think you could say about just about anything these days is not getting results fast enough. And to make it concrete, something that is really present and tangible for them.

Trish: Yes, absolutely. And another vehicle for it is story. And so, to your point, how do we get people to connect in a meaningful way. So first we have to have the vision for it. We have to have an understanding. What is the direction that we're trying to get people to go and why do we think that that's really important? And if just telling somebody what the vision is and why that's important, we have to do that, but it's not enough to compel people. Otherwise there's all sorts of human behaviors that we would do just based on information.

So, how do we have that vision and set that direction and then how do we help people connect with it. So it's orchestrating the experience and then it's also sharing stories. And the stories are things we can gather from internal to our organization, things that have happened that now make this an imperative. Or now illustrate whatever it is that you want people to connect with about being able to move in that particular direction.

So, briefly, a story that I was actually speaking with a couple of folks on a break earlier today. I've actually been consulting with one of the largest food manufacturing companies in the world. And they're at a point of bringing data analytics into their warehouses and their manufacturing process, and being able to use data informed decisions on all levels of the organization and especially throughout their entre supply chain.

So what does that mean? That means there's a big global initiative in being able to standardize on technology systems and being able to standardize on global process. And of course that can be challenging when your business unit and your geographic locations, your offices, and your facilities are not used to working together in that kind of a cadence.

And in this case, you're taking something, in this case, an organization that's been around for decades. And people, in some cases their families have worked for this organization for generations. So you have a lot of entrenched, there's a lot of entrenched systems and knowledge and this is the way that we do things and this is who I am and this is my identity. We talked a lot today about becoming. Helping people become. And ourselves included. So in that context, how do we help people, in a supply chain, in manufacturing environment, as one example, that the information that they're handling is just as important and needs to be handled with the same care as we do the physical goods that are going to be going through the supply chain.

And the way that we found to really do that was to take stories that we had gathered from internal to the organization, by actually going to the "gemba." Meaning to go out into, to go where the work is happening and talk to people and say "Well, why does this matter to you? Do you have a story of when its gone right? Do you have a story of when its gone wrong?" And then being able to tell those stories to illustrate. And in this case, we were track and trace, we were working on traceability and being able to trace back after there's been a problem with a food. There'd been a consumer notification.

And so one of the stories that we found was really very impactful was about a time when it went really wrong and if they had had, they in the organization, had had the information that is so critical to be able to trace back what was driving the root cause of a particular problem. Someone had something that was not supposed to be in their food that was in their food. If the organization had the appropriate systems and information at the time, and the data and analytics to get that kind of insight, they would have been able to make a difference to the consumer faster.

And people at this organization would cringe when we'd talk about this story. And we weren't there to shame anybody, that was not the intention, but the emotional encoding and the emotional impact is critical because, to your point, you need people to connect in a meaningful way. This is why it's important. And when they feel that emotion, in this case [they say], "I care about my job and I care about what I do, I don't want that to happen again. And now if you're telling me that this training that I'm going through, the support that you're providing me, these resources that the organization has invested in to help me now be more attentive to the information flows and the data flows." That's going to help people really be compelled and connect to what it is you need them to do next.

Julie: Yeah, I like that story because it makes it really tangible, what the impact is. And so, as you've been talking throughout the day, an example from my learning organization came to mind. So let me try this on and see if this fits what we've been talking about.

One of the challenges that my businesses had brought to me, my learning team manages learning for call centers, was "You [have to] cut down on the training time. It's too long." And I think anybody who does training for a call center has probably heard this. "It's too long. It's not that hard. You just [have to] get them out there. Why can't you be faster?"

And a big part of what we knew talking to our new hires was a significant factor in whether they were going to be successful was their confidence. And their ability to do the job. Are they going to know what to say on the phone? Are they going to what the answer is? Or know where to find the answer? Everybody knows what it's like to not have confidence. It's not a good feeling. To have that anxiety that you're not going to get it right.

Trish: Especially new on the job.

Julie: Oh yeah, totally. Where everything is new. Just the subjective "Let me convince you why I think this is true" wasn't really working. And so what we did is we built dashboards that would give us data about how they were performing. During their training and their on-the-job training period. And we showed, you know, you can say people performed differently and they learn at different rates. But to be able to show it and to be able to say based on real time data input we're getting.

Trish: Objective.

Julie: Objective data. We can give very personalized coaching where it's needed. And we can also, if somebody's mastered it and they're ready to go, let them go. Get them on the job and get them performing. But there's value in keeping the people in training who need more help. So that we can get them to the same level of readiness and you're going to ultimately get more value out of it that way. So that's the way that we approached using data in a real time way, and to be able to say, "this is why the duration needs to be what it is."

Trish: And you know, Julie, you're bringing up a number of really excellent points. And so one of the things is we're used to traditional training measurement and evaluation which is a summative evaluation process. We get to the end of something and then we measure backwards. We go, "okay, what's the impact study, did we hit the bel or not?" We're not trying to fix it anymore because it's reactive. It's retrospective, it's looking backwards. We've gotten the outcome and we either achieved success or not.

And so, one of the first things that people connect with when we start talking about collecting data in the dashboards in the way that you're talking about is, we can actually use data and analytics now in order to inform the solutions, the solution design. So these are the interventions that we're going to do. We know that these are potentially the best solutions out of all the things that we could do. Here are the things that we think are going to work for our people in this situation right now based on data. It's based on we've been able to do these analyses.

Now, the third thing is, now we can also use the data analytics to then optimize and pinpoint targeted interventions. So these folks here would benefit from additional help and from additional coaching. These other folks, they're already rocking it, we can let them go. Because there's nothing more frustrating than everybody just getting the same treatment when one size does not fit all. But now you're able to target your interventions and conserve your resources. So now the people who need it the most get what it is that they need, and the people who just need to get on with it, get to just get and go. And you're eliminating that kind of frustration.

So, and I think, now the solution you did there for your organization, was that kind of home grown? How did you build that system and start collecting…?

Julie: You know, it's a good question because it is home grown, and when I started leading the team, we had kind of the traditional measurement and evaluation folks. And they did all the traditional level one, level two, maybe kind of, sort of dabble in a level three, not so much. And the level ones and twos were on steroids. They were just insanely complex. And, but we still didn't know are people able to apply it to their job in the real world. It was sort of like, from the ivory tower, we're in a college classroom telling you how to design these things.

Trish: And this is an interesting study.

Julie: Which isn't real world. And I was like, look. We talked about leading indicators earlier today. For me, a level one and a level two, they're just leading indicators. They're not all of the leading indicators, but they give you some sense of is this going well? Is the probability of success higher or lower? If somebody on their level two exam hits the benchmark, that's good. That means they were able to retain what you taught them. Can they apply it? Who knows!? I have no idea. Can they apply it within the day to day emotional rollercoasters that happen in a call center? And everything's coming at you at once. We don't know that yet.

So it's a good data point that gives us some sense of where it's going, but we can't judge everything on that alone. So what we said was, "Don't create our own data. We don't need to go create our own data sets." And, in fact, our business is going to respond more if we take their data. And, by the way, that already exists. We just have to get access to it. And we have to be sure we know how to manipulate the data in the system, but it's not crazy complicated. It's tableau, and its systems that we have skill sets for. And so that's what we took in. And we measured them on the same measures that they would be measured on the job. Instead of trying to sell them on new measurements. Let's relate it to the measurements that are already important to them.

And so, on the survey, you know, I said one to two years, we're probably about two years in on this. We established our proficiency measure, which didn't exist. And now it's being applied across our global network of call centers.

Trish: That's amazing.

Julie: Now we have kind of these checkpoints, right? Where should people be? And when do you keep people back? Because you know they just need a little more and we've seen those success stories. You know, the first times, it was sort of like, "Oh man, I don't know. Let's coach them more and let's keep them longer, but I'm kind of nervous." They actually performed beautifully. And so it proved the case. So I think that's an example of the look back, but also using real time data.

Trish: Yeah. Both have their merits, for sure. And, something else that we talked about today and, I'm glad you're bringing this up as well. We don't have to jettison all of the stuff that got us here. So sometimes people go, "Well, the Kirkpatrick model and that's dated and da da da da da." And we look at other measurement and evaluation and traditional and stuff like that, but the fact of the matter is, those things can still serve us today. We don't have to get rid of them just because they've been around for some period of time. We can still leverage them.

But, to your point, they have to be positioned in the appropriate way. And so, the things, in order to do the transformation of ourselves, we can still take the things that still serve us with us and the things that no longer do, and this is an opportunity for us to review what's working for us and what's not and let go of the things that are not working, but then take those things that are still working, especially when they're still working and we have some comfort level around them, and take them forward.

That also means that we do have to do some of the new stuff and we do have to get outside of the ivory tower that we often call L&D (Learning and Development). We're not divorced from the organization. We're not divorced from the operational data. We're not divorced from our workforce and we shouldn't act like it. And so this isn't about L&D hoarding a bunch of data that we generated or that we've got trapped in our own technology systems. This is about coming up with good business questions, in this case, in the call center. Who needs help? And then being able to leverage whatever data exists from whatever data source and whatever domain in order to help us answer that question in a meaningful way using data science and decision science in a way that can help us then tailor the interventions and target the right segment of the audiences in order to be able to help them be better at what it is that they're trying to do.

Julie: Yeah, so I loved that you said that, because one of the things that I really preach to my learning organization is be a business leader first with a specialty in L&D. And you have to fully immerse yourself in the business, how they measure their success, what they need to achieve, how they look at both quality and how they look at efficiency. Because, that's where then you bring your L&D expertise to help solve those problems. And you're never solving them by yourself. There's always other pieces of the equation that you have to bring into it. And so if you can show up and intelligently contribute to the business discussion at hand, there's going to be more appetite for people to listen to the solution that you want to bring to the table.

And so that leads me to another question I had from earlier this morning. You talked about, you asked us actually, how much of this whole data science thing, this AI thing, this data analytics thing is math and analytics? And so the right answer is about 20%. And to your point, you don't have to have those skills yourself, you don't even necessarily have to have them on your team. You have to have access to them. Most businesses today do have access to those types of resources. But the other 80% is stuff that is already stuff that we do every day.

Trish: In our wheelhouse.

Julie: In our wheelhouse. And it starts with knowing what questions to ask and identifying what actually needs to be solved. We know a lot of times that people try and throw training as the solution to everything and we've learned and we know maybe it isn't always training. Maybe it's something else that is not working well in the environment. But that brings me back to the questions. If we're just starting to dabble with this notion of using data, using analytics, how do we know if the business question is well suited to bringing data to the conversation?

Trish: Really excellent point. So a few things there to kind of unpack. The first thing is, exactly. So analytics is a discipline. It's the same regardless of domain. There's nothing special about analytics applied to work based learning. I'm sorry to tell everybody but there's no… other than the questions that we're trying to answer. The types of questions that we're trying to answer from the frame of the learning and performance function would be, or talent development, would be along the lines of business questions that are usually performance based, right? We're trying to figure out something that's having to do with the performance of people.

And so we want to look for questions in the performance environment that matter to somebody that's going to make the investment and the commitment to take action. This is not an academic exercise. We're not going through an analytical process and analyzing, collecting, normalizing, and then analyzing the data just to create a cool algorithm so we can stand back and be like, "Ooo, look, cool algorithm. And look, analytical output. This is nifty." We need somebody to actually take that and actually carry that forward.

So, it starts with that. What the question that has to do with something that has meaning and matters to the business. That there's going to be somebody who has specific responsibilities around taking that forward. And that's probably somebody in the business, because we in learning often influence but don't have the authority for some of the actions that need to happen in order to really help move things forward. So those are some of the criteria around a good question.

And then we have to have really good skills in being able to facilitate a conversation with the business, right? And so whether that's leadership or that's front line managers or that's front line staff, whomever it is. It could be suppliers, could be customers. We have to be able to facilitate a conversation with them in a way where we're getting their insights out, because part of the question process is forming a hypothesis.

Okay, well here's our question. We want to know, as a question going back to your example with the call center in your organization. We want to know who's struggling so that we can identify and help, right? So we're not using it to be punitive. We're using it to be diagnostic so that we can actually provide some support, targeted effort, personalized effort, down to the individual. So "how do we identify them?" would be a really good question.

Then you have a hypothesis, you have thoughts, you've been working with this population, you work with other people that work with this population. What do you think are the factors that are involved that would be good indicators on alerting you to who's struggling and who's acing it. What are the factors that would matter? One of my favorite tools for that, that we perhaps don't often use in L&D, is a cause and effect diagram. Or a fishbone diagram. You know because then the head of the fish, we think about fishbones, de-boning a fish. The head of the fish is going to be whatever question or problem we're trying to solve, which in our case is usually a performance problem. And then each major part of the rib coming off the line of the fish is going to be a different area. So what are factors that affect the people? What are factors that affect the policy? What are factors that affect maybe well-being and health. Maybe there's a stress issue that's happening, right? What are the factors that are affecting the managers? Or whatever. We've got kind of the main bones and then we think about, well, what are the little bones that come off of each one of those little areas?

The object of the game isn't to create a beautiful fishbone diagram. The object of the game is to craft the good question, that we now have a hypothesis. We think these factors matter. We think some of these factors matter more than others. And now we can work with the data scientists to help us understand what data would need to be collected in order to test those hypotheses.

Julie: Or do we already have the data?

Trish: Well, we most likely have the data. We're awash in the data. But this now takes us out of a couple things. Number one, we're not just staring down data. And I think it was Mark Twain had the great quote about, "You can take data and torture it enough, to have it come out with any result or any kind of message that you want to." Of course, I'm paraphrasing. But it's also, we can look at the data that we have and we can stare at it long enough and see all sorts of different patterns, but it has no context, there's no meaning to that. It's just, you know, we can go tool around in the ocean and look at stuff but we don't even know what we're looking at if we don't have any context. And instead, before we even try to dive into the treasure trove of data that we are just surrounded with, how do we have the good question, the hypotheses and now go looking for the data that we need.

And in that case now, that takes us off the hook on having to fix the world's problems, which are data quality and our technology systems, before we can start doing something meaningful in the analytics domain. We don't have to fix all the underlying technology architecture. We don't have to clean up all our data in order to get started. We just have to have access to the technologies that are going to give us the data that we need in order to answer this question and frame this hypothesis, fuel this hypothesis, and we only need to have data clean enough to be viable to be used in this particular situation.

Now that's true starting out. If somebody's watching this and just want to get started, then we can do that as something that we can do now because it really narrows the scope and really gets that narrow focus and now we need to manipulate this rather than feeling like we [have to] clean house and full housekeeping before we get everything started.

That being said, ultimately, we need a more mature workbench as time goes on because it's not cost effective for us to do just kind of those spot checks. We need better tools and technology to be able to clean up that data. We need to continue to work on getting better at the data that we're producing, the data that we're collecting and have data quality management in place and so on and so forth over time. We don't have to do it right at this particular second. But that 20% of that data science and the math and the statistics and those analytical models that are based on algorithms that we can work with data scientists to help us craft. That's that middle bit that happens there. And yeah that's only about 20% of a project.

We now have analytical output that comes from that. It goes, okay, we'll process the data. We've tested your hypotheses, here are the results of that test. And there are going to be some things that we're going to discover. We are going to find out in our hypothesis that we worked with others on, "Hey we're on point" for some of this and other stuff is going to be like, "Oh wow the data tells us that this factor actually matters more than this one. Huh, interesting."

But now this is where, I call it the bookend. So we did the question and the hypothesis, we had all that mass stuff that happened in the middle and now we've got the output and we need to do something with it, those are the bookends. And that now comes back to us to say and here are the insights. Somebody needs that insight in order to make a decision or decisions that materially matter to the business.

How do we then compel that action? And if we did that due diligence up front, and started with questions that somebody is in charge of taking action on with the insights from the data, we now have a sort of ready-made change champion, because we're changing behavior, and it's going to happen. Because you're not done with an analytics project until somebody has taken meaningful action based on this whole process that you've gone through in order to generate those insights. We're not done, it's not just about moving data to insights, it's about moving insights to action.

Julie: Absolutely. Absolutely, that's true. One of the things that's going through my head when you talked about the process of starting with the fishbone, I think that's really smart and I think that's probably a good starting place. So let me just share an example with you of something that we did in my team where we didn't do that. Not to say we didn't have a lot of conversation about what we were trying to solve, but I think we could have made it easier for ourselves. So what we wanted to do was reduce attrition with our call centers. We wanted to predict who was going to leave and identify what factors were most predictive so we could get in front of it and stop them before that happens.

Trish: Or let them go.

Julie: Or let them go. That's a really good point. If somebody's not a good fit for the role, for the company, for what have you, for a number of different reasons. It may be you don't want to try and retain them. But what we actually did was we actually, and there's a lot of data. I think the team looked at a hundred different variables, right? There were literally… we have like 99 variables that we are looking at to see, is it location, is it tenure, is it team leader, is it rating, is it promotion, is it all of these things? And all of a sudden they had a list of ninety-nine, a hundred of them. Most of them didn't matter at all. And so, then you get down to this handful, and some of them are surprising, and some of them are no-duh's. But what I'm reflecting on is could that fishbone exercise have helped us skinning down…

Trish: …to start with.

Julie: Do I go after a hundred or do you go after the twenty-five that are the most compelling? But we don't know what we don't know. So is that the place where you ideally have a data scientist to consult with?

Trish: So, I'm making a generalization. I'm going to make a general statement and I mean no disrespect to any data scientists out there, but data scientists are trained to create algorithms. They're trained to identify factors. So sometimes data scientists fall into that same loophole. Let's go find all the cool factors that might be out there and gather all the data that we might use to create a pretty cool algorithm. And that's not, we're not trying to create a cool algorithm. We're trying to get a business result.

So sometimes that relationship needs to be mediated. So that's where we can, as a learning leader working with our teams, help get our teams focused on, "We're not trying to do an academic exercise. No one is going for a PhD with this, in this context. We're getting to a business result at the lowest cost. Right? So what's good enough, progress over perfection, that's going to help us get there?" And because it's not a scavenger hunt to go find all the possible factors that are out there and then whittle it down. It's defined enough that we think is reasonable to create, to work with the data scientists to create the algorithm to test the hypothesis and then figure out from that collection which are the ones that matter. And especially when we're just trying to get started.

So often times in new analytics projects, when we're just trying to get this done, we want to do something that's way less than 90 days. If you're looking at, "Oh well we're going to, we've identified 99 different variables and now we're going to have to go get the data for that, which means that we're going to have to get past the gatekeepers that have access to the data. And we're going to have to get that data and then clean that data up," that's probably going to exceed ninety days. So if you're just getting started with this… so then how do we put in guardrails, right? How do we say, "Okay, here's how we're going to get this started." And we can moderate, we can adjust. But just to give us our own indicators to go, "Okay, well, here are the boundaries that we want to go ahead and set."

So then that can really help. And that's always going to happen, even if you look at, like if you had research in an organization that was similar to yours and discovered what factors they had in their flight risk algorithm, and given everybody flight scores. One of the famous case studies is HP doing that, figuring out and then assigning each employee a flight risk score that their manager knows. And then you get to make a determination on whether or not you're interested in trying to have interventions to keep that person, to encourage them to stay. Or if you're willing to just let things play out and let them go. Because those are the good decisions that we're trying to make based on our judgement, based on the analytical output.

We can look at other models that are out there, but what we're going to find is we can use the same factors and gather the same data. But the waiting is for us, with organization and our people, and this particular population. Don't be surprised if that's different.

And a last thing, Julie, while I'm thinking about it, we also often think that is has to be big data. There's nothing wrong with little data. And big data is actually data that is unstructured. When you take a sampling of big data, and get it ready to be able to be used in an algorithm, it's no longer big data. You've already fished out of the massive ocean of stuff, and have prepared the data in such a way that it's no longer… it came from big data but it no longer is big data when it's ready for processing, when it's ready for analysis. So there's nothing wrong with little data. So going back to what you were talking about like with the Kirkpatrick model, method, there's nothing wrong with the Kirkpatrick model and some data collection instruments that perhaps we've already used in the past and data that we have amassed that we that we might now include in a data set depending on what we found in our hypothesis.

And that being said, we can discover the factors based on our own experiences and brainstorming with others that have some experience in whatever problem we're trying to come together on. We can also research what are other factors that other organizations, perhaps have used. And then we can also use artificial intelligence, sometimes, if we have the right tools, the right AI tools, to actually take a large set of data, big data, a sampling of the big data, and actually, it discerns what factors matter the most. It looks, the artificial intelligence looks for the patterns and then works backwards and says "here are the needles in the haystack that actually matter the most." So those are three different ways that we can do it, but we don't have to have the artificial intelligence, and we don't have to have the big data to do it. We can use research and we can use expertise and experience to craft those hypotheses and then use an analytics approach in order to test using the data we have.

Julie: Yeah, so I think that's really encouraging, because what we saw in the survey earlier today was, I think roughly 20% of the audience hadn't even started thinking about how they make a foray into data and data analytics, and another 20% were ready to start. So, you know, I think that's pretty common. And so these are really accessible, actionable methods that we can start to apply on top of what we're already doing. And start to move in that direction, without feeling like you have to upend everything that you've done and come up with all new methods.

Trish: We can think of it from the frame of you're starting an R&D (research and development) initiative. You're doing research and development within our operational practice. So L&D, operations, our operating model looks like this right now. We're going to preserve that because that's also what our stakeholders expect from us right now. And then we can start at a kind of R&D function and we can experiment. And in that experimentation, we can stay kind of in stealth mode at first. We can use operational data but we can kind of get our feet under us first as a team, as a learning organization, get some ideas, and then go ahead and kind of market test it, right? Market test it with our audience, with our internal stakeholders, or external stakeholders if you serve the external customer. And then we can take a look and we can mediate and decide when it is we're ready to go and kind of show off what we've done.

But we come… corporate training comes out of academia. And academia has, in the western world historically celebrated the right solution the first time out. Going through an academic process like earning a PhD, you go through, and go through, and go through iterations that you don't publish until you've gotten it perfect. And here, we're kind of flipping the entire apple cart. Because our ADDIE model in instructional design was also kind of about perfection. We started with getting the requirements up front and then we kind of made sure that we had those nailed and we didn't create or develop assets until we felt comfortable. That's what waterfall methodology is all about. You don't start the next phase in the process until you've closed this one out exhaustively. And that worked for a time when we were building things to last.

Now instead we need small experiments fast, things that we can do to be nimble and agile. And not just agile the methodology but, agile, like to be nimble, to move with speed. And we have to learn, like engineers, to get good at failing. We're going to expect that the experiment is going to fail. We're going to learn from that, and then we're going to have an opportunity to make it better.

Julie: I love that you said that because the example that I shared with trying to get a predictive model for attrition came as part of a much larger initiative around employee engagement or retension. Making the company a great place to want to work. And we did fail. A lot. And for my team, first of all, they're not used to failure. They're used to, you get everything to perfection. They're not used to exploring different ways of doing things and I found that a big part of my job was I had to show them, "No, there's tremendous value in failure. Look at everything we know now that we didn't know before. Now, the scope of our problem just got smaller. Because we can check these things off the list. We know what doesn't work." That's just as valuable as what does work. Don't view that as, oh my god, we failed. You're chipping away at it. Some of these problems are big and they're going to take time and you should expect that you will fail along the way. And that's good. That's good.

Trish: That's progress.

Julie: That's progress. And I think this is the perfect place to segue into thinking about the skills and capabilities we need with our learning professionals and even with ourselves. I love the idea of going into silent mode or your stealth mode off on the side.

So how do you know who you've got that's equipped for that because there'll be a lot of people that hold up their hands to do it, right, who are just eager and they want to go out there. And maybe that's a big piece of it. But what are some of the core competencies and how do we think about developing them? Helping our staff acquire them. You talked about the citizen data scientist.

Trish: Yep. From Gartner.

Julie: So how do we identify are there inherent qualities somebody might have? Maybe they don't, they're not steeped in a particular methodology or skill set yet but they've got the capacity for it.

Trish: Sure, so we can unpack all of that. And I want to actually, you brought up Gartner Group's idea of this citizen data scientist. I want to, I took my phone out to make sure we have the official definition of it. So, the Gartner Group defines a citizen data scientist as a person who creates or generates models that use advanced diagnostics, analytics, or prescriptive capabilities, but whose primary job function is outside the field of statistics and analytics.

So again people can be the math nerds but they don't have to be. We can all play in this. And as we talked about earlier today, as you're bringing up, we can all be really good citizen data scientists, right, because we can come up with good questions and hypotheses and help take the analytical output into the organization to get action done.

And part of that, just to touch on, and this is actually from the Gartner Group website, Gartner also says the reason we can do that and be successful there is because we can outsource either, or insource to another group within our organization or outsource to a person or a platform because there are lots of analytics platforms that are available now, data science platforms that are available now. But Gartner says more than forty percent of the data science tasks will be automated by next year. By 2020. That's going to increase the productivity and broader usage of data and analytics by citizen data scientists because we're not going to need to have… but we don't need to be as numerate as perhaps we may think. We can leverage those other kind of modalities.

So that being said, how can we take a look at what are the skills, or competencies and capabilities? That's what we've been talking about. What are we trying to do? So as learning leaders, there's a difference between building an analytics practice and applying analytics to a project. And we can do both, again, in parallel. But what are we doing? Because then that's going to inform what team members do we need on the team to do either one of those things.

And we're probably going to be doing both in parallel. Get started on a project because people need to have that experience, our team, ourselves included. We need to go through the experience together. So how do we have a project that's small in scope, less than ninety days, something that's got kind if a quick hit. It's meaningful. There's some impact on the other end. And we can do a quadrant. We can put together a little quadrant that says, okay, where's kind of the low hanging fruit, right? Where things are going to be low cost, not a lot of effort, but have some kind of impact to it. And we can kind of map a couple of those things out, come together as a team and as leadership and say let's start there. And then, meanwhile, I'll take a look at that long roadmap of two year run in building an analytics practice within the organization within the L&D function. That's a two year roadmap. So if you've got mini roadmap, longer roadmap.

So mini roadmap, this is going to give you an opportunity as a leader now too to see where people are at. You're going to have some idea. There are some tools and certainly some capability frameworks that we can use in order to really assess people's skills in different roles that were kind of necessary on the team. But, now you're going to find out, who's good at collecting? Who is good at identifying the questions? Who is good at facilitating the conversation with your stakeholders to draw those questions out? Refine them, better articulate them? Who is good at the math? Who is good at the statistics? Who is good at the data science side? Who resonates with that? Who is good at building the algorithms? Who is good at figuring out the different analytical approaches in order to apply in that particular situation? And then who is good at taking that analytical output and championing that in the organization to help people learn?

Because this is new for many people throughout the organization, of course us included. How to make better decisions based on data. How to help people trust. How to help people be informed. How to help people not be so scared necessarily if the stuff that's being created, you know, often times by the machines, often by AI driven platforms. But how do we help them socialize and then drive action. Because, again, we're not done with an analytics project until we've taken it all the way, we've moved data to insights and insights into action.

So, there's that piece. And then there's also a piece… so, I had the privilege of actually working with the Learning and Performance Institute based out of London. There was a global steering committee that, we all got together last year, about this time last year was when we started the project. And we all volunteered our time. And we worked with LPI in order to create a new capability map that identifies the capability areas for the modern learning department. And analytics is one of the big capability areas. Technology is another big capability area. And I'm really proud that I lead both of those working groups.

So, what I mean by that is we had working groups together. Different sectors, different industries represented. As a matter of fact, Brandon Carson who was the summit speaker last year, was on my technology working group. I asked Brandon to join us because of course his insights and experiences. And so we, not only from our own experiences, but data that we gathered individually for our capability areas, and collectively as a steering committee came together and said, "Well here are the capability areas, here's what we should name them."

And the capability area in that map by the way was not called learning analytics, it was called data analytics. And again, very deliberate and intentional in the name to be like, "Okay, guys. It's the same." We need to have an understanding that it's the same. But it's in an application. We have the domain knowledge and the learning science, and those pieces then help us view it through this lens. But the methodology is the same. Exactly.

And then we defined the capabilities and then the skills and the competency statements that are actually in the map. And the reason why many of us, myself included, volunteered our time to do it is because that assessment is free to everybody around the world. And so if people such as yourself, people watching this want to be able to use a tool, to do an assessment, or have their team individually go ahead and asses themselves, what'll happen is it'll assess them against the capability map and then the online system. You can just go out to the LPI's… if you just Google LPI capability map and we also had it in the handouts today. You can take the free assessment online and it'll create a personal competency profile report that gives you your baseline and then also shows you like, You're here and here's where else you could go."

And then now as a learning leader you can sit down with your team and say, "We're going to work on your individual or independent development plan and we're going to use this as one input." It's not going to be everything. And then you as a learning leader can also take a look at, now, across your team, maybe there's 80% of them that need better use of data individualization or storytelling or whatever it is. Now you can make a decision on how to invest in the team that's going to give you the best bang for your buck in helping the entire team move forward because it's a common gap in that particular area.

Julie: That is excellent. I'm for sure going to go check that out.

Trish: Cool. There's one other thing I wanted to bring up really quick too. We had it in the handouts and I'm sure as part of the video I'm happy to make the PDF file of the handouts available. But I also had the privilege of IEEE (Institute of Electrical and Electronics Engineers), the software engineering consortium, actually created a role a couple of years ago called a learning engineer. And they said okay if we in learning looked at learning through the eyes of an engineer, how would that be different than how we have historically done it? Which I thought was great because I created the learning engineering framework for the same reason, I'm a daughter of an engineer, a few years ago in order to do just that. Because, again, engineers look at failure. They look at input. They look at throughput. They look at output. This is the perspective that we in L&D, this is one of the mindsets, one of the new mindsets that we need to adopt.

And so IEEE created this learning engineer and we just had a conference in Arlington, Virginia, just this past May, for the community to come together for the first time and really start to put some momentum behind, "What do we want this thing to be? What do we think it needs to be? What is this role? What is this learning engineering practice? How does that fit?"

And so, what we've come to so far is, I think it's a cool little infographic because there's somebody who sketch noted it, and I gave them credit in the handout. But part of the conversation is now captured in an infographic based on a sketch note that came out directly from that meeting that we had in Arlington which was the first gathering ever of all of us to have the conversation. And it basically says well a learning engineer is somebody who knows the learning side of it, knows the business acumen side of it, and then also knows the engineering side of it which would be artificial intelligence, data analytics.

So now, where do we wrap our heads around the instructional piece, the learning sciences, the learning theory, the business acumen and also all the technology and technical pieces that are coming into play. So we're going to have a different scale. There might be some learning engineers that at least have an appreciation for the analytical algorithms and artificial intelligence. They're aware, but maybe are not get your geek on deep into that particular area and we've got others on that spectrum who are, but it all becomes part of that tool set.

So I really wanted to make sure that we had representation today on some of the latest and greatest research that's global that's out there to say okay this is how things are shaping up and who do we need to become?

Julie: So that's really interesting. What that make me think of is something that I often refer to with my team as systems thinking. And what I tell my team very specifically is don't stay in your lane. Nobody does anything cool by staying in their lane. You've got to think about your inputs and your outputs because you don't get to be successful all by yourself. So, from a new hire perspective, my input is whoever got hired by the recruiting team which doesn't report to me. And if they're not hiring the right profile, then I'm sub-optimized. I'm only going to be able to achieve so much. Because the raw ingredients, which is people, they weren't the right ones for the role and the company and all of that.

And so we have to care about that. We have to have a point of view and we have to influence what that profile looks like. But then the output is equally as important if we go back to time to proficiency and I get them X far through training, and then that last 10-15% percent they need to achieve on the job with their team leader. But it's simple stuff, like, are they ready for them? Do they have their own desk? How much have they met with their team leader and their coach? Are they being engaged within their team? This is simple stuff but a lot of times it doesn't happen. And so, even if my input was good, and my piece was good, but if then my handoff falls flat, the whole thing still fails. So, I not only have to care about the input and my part, but I also have to care about who I'm handing off to because I'm still accountable for it. And so that sounds to me like what you're talking about.

Trish: Yes, exactly. It's an engineering system and that also gets into what we've been talking about all day which is closed feedback loops as well. So systems thinking is the interconnectedness of things, right? So the throughput and the output don't exist independently of the input, right? It's heavily influenced by that.

It's also, that system that you just described doesn't exist in a vacuum. It doesn't exist in space where the conditions are static and don't change. It exists within an organization that is changing all of the time. And so that system, that continuum that you have just laid out, Julie, is susceptible to the environmental factors and as the conditions change. Like, we were talking about the "Happy or Not" buttons in the airport, in the airport washrooms. When the conditions of the washrooms change, they need to know about it so they can send a crew in order to be able to service the washrooms. When the conditions in our system change, in that instructional system or learning and performance system change that affects our outputs and our outcomes, we need to know so that we can do something about it.

Julie: This is where I think learning can play a really, really pivotal, influential role. Because if you break out of just focusing on your learning component, and you start talking about those critical components that go all the way through, starting with recruiting to what you do to when they're in their jobs and what kind of support, whatever roles they are that they're getting on the job. If you can find those data elements that are constants throughout it, then everybody knows when the red button gets hit, it's important to all of them. And they understand the impact that it has on all parts of the chain.

Trish: Downstream and upstream. Absolutely. And that's where I think the talent management, integrated talent management models can be helpful. So, of course I have a picture in my head. It's the bookends. To your point, there's the recruitment piece, the talent acquisition piece that's upfront, and then there's the talent retention piece that's kind of at the end here, and then there's stuff that happens in the middle. We like to call that talent development. We also like to call that learning. How do we get them? How do we keep them? And I'm like, great. What are we going to do with them while we have them?

And what's interesting too along with that is, not only is that exactly the right frame, to go meta, right? To go outside of ourselves, and have that broader perspective, and have an understanding of how those upstream influences from recruiting or talent acquisition play into the talent development then play into the talent retention, the bookends. But then also what that gives us is, it gives us the ability to be able to optimize across that entire stream. To be able to understand those milestone events and how those factors are influencing each other. And again, like to your point, we may not have control over all of that, but we should at least have visibility into all of that and be doing a readout of all of that. And it positions us as not being in a silo but being a strategic partner that's playing with the other strategic partners in a meaningful way of contributing to the success of our people and to the success of the organization as well.

Julie: We're probably ready to move on to our evening activities but I just can't thank you enough. This has been just a really stimulating conversation. I know it's definitely got my brain really moving in a bunch of different directions and I know I'm personally taking away just a ton to think about and work on so thank you for your time.

Trish: I really appreciate it and I think, at the end of the day, all we've ever wanted to do is to have impacts, is to really help people be successful and to feel like we're making meaningful, measurable contributions to the organizations whom we serve. And this is a way of us being able to do that and helping everybody just work better.

Julie: Well, thank you.

Trish: Thank you.