# **MGT 8803 SUPPLY CHAIN MODULE**

# **Week 10 TRANSCRIPTS**

## Bullwhip Effect

>> Welcome to this lesson on something called the Bullwhip Effect. And the Bullwhip Effect is probably one of the most famous supply chain concepts. And so for here and in this lesson, our objectives are going to be to discuss what this thing is called Bullwhip Effect. Then go into what causes the Bullwhip Effect to occur.

And what are some ways that companies try to mitigate or deal with this phenomenon called the Bullwhip Effect. A professor by the name of Professor Hau Lee is credited with identifying this Bullwhip Effect or what's known as the Bullwhip Effect, after observing a multi-echelon supply chain. And by multi-echelon, what I mean is much what we saw on some earlier lessons, where maybe you have a supplier here, it's a given company, this supplies to the say a wholesaler and that wholesaler maybe supplies to a retailer, who supplies on to customers.

So when I say multi-echelon, I'm saying multiple levels in a supply chain. And he was studying, by the way and first documented this problem with Pampers. And what he was saying specifically was, there would be small changes in demand at the retailer but he was noticing the wholesaler was ordering more and less frequently large orders.

And is if you went back to the supplier, we're seeing even larger fluctuations in changes in order. And by the way, this phenomenon was found to occur in other industries, other products such as HP Printers. So to look at this in a more graphical way, to illustrate it, right, the notion.

And what he saw was that, the magnification of orders as you moved upstream. And so we when we say upstream, we start with the customer. And if you go back, the supply chain toward the manufacturer that's considered upstream. He was seeing the magnification of orders as one moves up.

So for example, if the demand say again, for Pampers was forecasted to be 10, the retailer would order 15, in order to have some safety stock. And when they would place that order for 15 to the distributor, the distributor says, okay, you just order 50, well, I'm gonna go back and order 20 from the manufacturer.

And then the manufacturer in turn would say, 20, well I'm gonna order 40 from maybe whoever my, right, we'll call it raw materials suppliers, which isn't on here. And so you notice there's this amplification, right? Of quantity, amplification of order size, as you move up the supply chain.

So what causes, right? So the really kind of the key question then is okay, if there's this increase in order quantities as you move upstream and a supply chain, what is causing this behavior to happen again in a multi-echelon supply chain? And there's four big causes to this.

The first is, when there are fluctuations in prices at the retail level, meaning items are placed on sale. You know when the price is reduced, when it's placed on sale, the price is reduced and the demand typically goes up. But that demand is not going up because people want more of it at the retail level, it was going up because the price has been lowered.

And so we're calling that, creating artificial demand, okay? But the problem is, that the retailer if they put that item on sale, and it increases demand, the wholesaler doesn't know that the retailer did that. And the manufacturer doesn't know that the retailer did that, right? So the upstream levels in the supply chain look at this bumping demand, and think it's not artificial demand but actual demand.

And so, they ramp up in response. So price fluctuations can cause this, right? Another thing that can cause these fluctuations is just order batching, right? Where if a company is ordering infrequently in large amounts, those upstream in the supply chain can't distinguish that change in batch size from a change in demand.

You've changed your inventory policy at the retail level. You wanna order more, less frequently, so you place in your first large order. That wholesaler doesn't know why you've done that. They assume again actual demand is up. Not that you were changing your ordering size. A third cause is called here shortage gaming.

And this is where a company orders more than they think they're gonna need just to be safe. That's this one right here. A buyer orders way more than they need. And then if demand starts to come in, as being less, they start canceling orders. Well, the problem is that upstream of them has already begun to work to fulfill the order that has now been canceled.

And then of course the forecast here is forecasting inaccuracies. If there's not good predictions of what demand's gonna be, companies will tend to over, can rather tend to over order. So what can companies do to try to mitigate or to try to lower this amplification of order sizes as you move upstream the supply chain?

Clear first an easy thing is you need to do a better job of giving that information that's occurring at the actual customer level, which will call point of sale POS, point of sale data, so that the actual sales data at the retailer take that information and give that information to the wholesaler.

Give that information to the manufacturer and so on, so share that point of sale data backup supply chain. Other ways to mitigate, if order and costs are problem, reduce the desire, reduce the incentive for a person downstream of you to want to order larger batches, right? And then if discounts, promotion, sales, create artificial demand, then eliminate them.

Don't use them, try to discourage them. So that that artificial demand isn't occurring as often. So it's interesting to kind of think about how having a better information, in terms of point of sale data, having better information can lead to mitigating and reducing some of these issues associated with what's called the Bullwhip Effect.

It's also kind of interesting, and I would encourage you to kinda think about how can analytics and having more data, like that point of sale data. And doing more research and study and analyzing of that data, how can analytics help lead to even further reducing the Bullwhip Effect.

And making for better, more efficient supply chains.

## Newsvendor Model

>> Another very famous and well-known concept in supply chain is something called the newsvendor model. So in this lesson I want us to go through and understand exactly what this newsvendor model is and how it's used. So while it's not seen as much these days really if at all, newspaper or news boys, right, were a very common sight in city street corners for many years, right?

And the key question in this picture that this newspaper boy had, was how many newspapers should they buy? Should he, rather, buy from the New York Times every morning, or whatever local newspaper it was, right? Cuz see, the challenge that he faced, and I'm making up some numbers here, but the challenge he faced is, he can go buy a paper from the New York Times for $0.80.

And then he can take it down to the street corner and he sells it for $1.00, right? And so there's a dilemma that he faces. If he doesn't buy enough papers, too few papers, then he'll run out. And there will be customers who will show up to get a paper and they won't be able to buy it and there'll be profit that is lost there, or a sale that's lost.

On the other hand, if he buys too many papers, right, then he's gonna have to eat the price of the papers that he doesn't sell, right? Which will lower his profit. So this leads us to a situation of what, kind of, is the framework around when this newsvendor model would be used or where it would be applicable.

In a supply chain context, right, what you're looking for is a situation where the company has one chance to decide on a stocking quantity, right, for a product you're selling. And the demand for that product is not known. It's uncertain, it's unknown, but there is some sort of probability distribution.

So you know with a certain probability, a range of demands that may occur, right? And in our case here today, we'll look deeper at normal distribution, right? The known profit for each unit sold and the known loss for a unit that's not sold are known. We'll call it marginal profit, marginal loss.

And overall the goal here in this context is to maximize expected profit. I'm using that word expected here so you should be thinking, okay, when I see expected something, I'm probably gonna have probabilities in here. So probability times a value, and that is indeed the case here. Actually turns out that there is a lot of areas where this can be used, far beyond just newspapers.

So for example, if you think about a cafeteria that sells food, right? They wanna have enough food on hand to meet the demand for people who come in for lunch. But they don't wanna have too much, right? They have too much food, they gotta throw it away, there's waste.

If they have too little food, then they have people who don't get to eat and they don't get that revenue from those individuals, right? Same with dairy foods, right? Dairy products are perishable, they have a limited shelf life, right? You don't wanna have too much milk, it goes bad.

You don't wanna have too little milk, if it runs out then you lose, again, sales. Also items that have a short selling season, right? Christmas trees here in the US, you cut them down you put them out on a lot, you got a limited time to sell them.

Once Christmas hits, demand for cut trees is pretty much zero. Same with flowers on Valentine's Day, right? Or even fashion clothes you could consider, and of course newspapers all right? So let's go through here and define some variables. And we're gonna define here and I've got them here listed, but we're gonna say c is gonna be defined as the cost to purchase, the cost of buying an item.

The cost of buying a newspaper from the New York Times. The cost of buying a Christmas tree from the Christmas tree farm, wherever it is. p we're gonna define as the selling price. How much do our newspaper boys sell each paper for? How much do I sell the Christmas trees for on my lot that I have down here on the local corner?

s we're going to define as the salvage value. So in terms of newspapers, at the end of the day, if I, the newspaper boy, have extra newspapers left over that I didn't sole, sell rather. And I can go down to the local pet store, and I can sell those for $0.05 each to the pet store, cuz they'll use them, that's my salvage value and they'll buy whatever I have left over, okay, salvage value.

x we'll say is the number of items that the newspaper boy decides to buy on a given day, and P will be the probability. Keep this in mind, the probability that the xth item is not sold, the probability that the 10th paper is not sold, the probability that the 11th paper is not sold, right?

The probability that the 12th paper is not sold, so you get by the way, as x gets bigger, the probability of it not selling is also going to get bigger. So, I'm gonna go further here, all right? And I wanna come up with two values, and I'm gonna call them the overage cost and the underage cost.

And I'm going to define the underage cost, right, as, what does it cost me every time I have unmet demand? Or put another way, what's the cost per unit for each paper I don't have that somebody wanted to buy, right? And each unit that I don't have that somebody wants to buy is the price that I paid for it, I'm sorry, the price that I sold it for minus the cost it took me, right?

So in the early example I used, it's the $1.00 minus $0.80. Every paper I don't sell, there's an underage cost. And then on the flip side, every paper that I have too many of, right, I have to eat some money. It's gonna cost me, having too many, overage, having too many papers cost me.

And that cost, for each paper that I have too many, is the cost for one newspaper minus its salvage value, right? Now you remember before we said we want to minimize, right, I'm sorry, we want to maximize the expected profit, expected profit, right? So if I think about this, and keeping in mind that as the probability of not selling the paper gets greater, the more of them I have, right?

So the probability of not selling one paper is very, very low. The probability of selling the 50th paper in my stack is higher. The probability of selling the 1,000th paper, if I stock 1,000, is really high, of not selling is really high, right? And if I'm talking about expected profits, then right, the probability of not selling it times the overage cost, right, is gonna give me an expected cost of having too many.

As long as, though, that value is less than or equal to, 1 minus the probability of not selling it times the underage cost, I'm gonna keep going. Now, let me show what I just did here, okay, with this equation, okay? In probability, you know that the sum of all possible outcomes has to come out to be 1, okay?

This is the probability of, right, probability of not selling the paper. The only other choice is that you do sell the paper. You got two choices, you don't sell it, you do sell it, okay? Not selling it plus selling it equals 1. So the probability of not selling it plus the probability of selling it has to add up to 1, okay?

So another way I can write this is instead of saying the probability of selling the paper, it's 1 minus the probability of not selling it, okay? That's what I've done here. And the reason that I'm doing this is because, what I can do now is, I can solve for the probability of not selling it.

And it's gonna look something like this, all right? cu over cu + co. And that ends up getting called the critical fractile, right? And it's kind of interesting to think through what we're doing here and what we're saying here, right? Which is we're now looking at a probability of not selling and figuring out where that point we reach, right?

In terms of should we buy one more, should we buy one more, should we buy one more? We're gonna keep buying, right, based on knowing the cost of having too few and knowing the cost of having too many. We're gonna keep buying, if we wanna maximize profit, until we reach this ratio.

So now let me put the rest of this up here on the screen. So now I'm gonna use slightly different nomenclature. What I've done here is, instead of saying the probability of x, it says here that the probability of demand being less than the quantity ordered. If the quantity ordered is bigger than demand, right, that means I'm gonna not sell.

If quantity that I keep is bigger than demand, there's gonna be some that I haven't sold. So the probability that demand is less than or equal to Q, is less than or equal to this critical fractile, this is the critical fractile right here, okay? Now we can go a step further and say there's gotta be some function that's, right, where Q is the variable in it, that also equals that.

So now let's go to normal distribution, okay? And let's look at this in terms of a normal distribution of demand. You know the normal distribution, I've got it here, that's that classic bell curve. Here it is right here, as I try to somewhat trace it. Ideally that with that critical fractile, what I'm getting at is, I want to choose a quantity, in this case of newspapers, where the probability of not selling is equal to the critical fractile.

Because that's going to maximize my expected profit, okay? And if I do that, right, what I'm basically saying is, if I'm looking at a cumulative standard, I'm sorry, area of the cumulative standard normal distribution, this whole area that I had in white, I'm now gonna crosshatch it blue, right?

Is the probability of Q being greater than demand, and then the smaller chunk ends up being where we expect demand to be greater. So here's the thing, it turns out that, right, mathematicians have determined hey, you can calculate, actually, this area. You can actually figure out what this area right here is, okay?

And it's basically, if this is a normal distribution, you'll have something called the mean which we'll call mu. And you can calculate a Q value anywhere along here. And Q is gonna be equal to the mean plus some z score times standard deviation. And it turns out that G(z) is what's called the cumulative distribution function.

It allows you, at any point here, to figure out how much area under the curve you got so far, going from left to right, how much area you've covered on this normal distribution or bell curve. So if we know what that value is, the probability that is the critical fractile, Whatever that ends up being, we can determine what the value for z would be from what's called a z table, or an area of the cumulative standard normal distribution table, you can find it online.

Or you can actually even use Excel, and in Excel you could use something called NORM.S.INV. And if you put in the critical fractile into there, it will give you back the corresponding z value. So if I know the mean and the standard deviation of demand, right, or a probability distribution of demand, right, cuz demand can vary.

And I have information, again, about how much it costs me to buy the paper, how much I sell it for, what my salvage value is, I can determine this critical fractile right here. I can plug it in to Excel or go to a table and get z, and I can determine how many papers, in this case, I should sell to maximize my profit.

All right, so this might seem like a lot for one lesson, right? So, don't worry, relax, what we're gonna do in the next lesson is we're gonna look at a sample problem and go through it with a sample problem. And what's really kind of neat about this is, once you see how to do these kind of equations, they're very simple, right, and they give you very interesting results.

## Newsvendor Example Problem

>> Welcome back to our series on supply chain management. In this lesson, I wanna use an understanding now of the critical fractile in the newsvendor model, and put this into context to solve a problem, so you can see how it could be applied. And in this example, we're gonna take on the role of a merchandise buyer for, say, the Georgia Tech bookstore, right?

Georgia Tech, it turns out, maybe in this scenario, is going to play in the Sun Bowl, right? And so you need, as the merchandise buyer, to decide on a T-shirt order for the Sun Bowl, right? And if you order too many shirts, you're gonna have leftovers and it's gonna cost money, right, your costs are gonna go up.

If you don't order enough of these shirts, then you will miss out on potential revenue and buyers, right? So again, this is an example of a product with a limited selling season. This product primarily will be hot up until the point of the Bowl. And here are some of the data that you have at your disposal, okay?

The T-shirt vendor who is going to make the shirts for you charges $6.50 per shirt, okay? You are going to sell them for $8.95. Once the Bowl game has occurred, right, demand will go away. And there's a company here in the US called Big Lots that will buy any leftover T-shirts you've got, but they'll only buy them for $1 each.

From past Bowl games, you've noticed that demand tends to be normally distributed. And you expect there to be, and with that normal distribution, what you've seen is a mean of 20,000 T-shirts, again, from past orders, and a standard deviation of 1,000. So now the question becomes how many T-shirts should you order?

So what I'd like you to do is go back to the equation for critical fractile, or I can give it to you. The critical fractile is CU over C0 plus CU, calculate the critical fractile, either use an area of the cubic standard normal distribution table, or you can use the Excel function of Norm.S.INV Use that to calculate the Z-score.

And then use the fact that the quantity you want to order should be equal to mu plus z times standard deviation. So again, trying is the best way to learning and doing is the best way. So pause this for a second, try to calculate it out, and then continue on.

Okay, let's go through the solution of this problem. So we're given here that we're buying from the vendor for $6.50 each from the T-shirt vendor. We're gonna sell them for $8.95 and we can salvage after the ball game for $1 a shirt. So salvage value a dollar, c, 6.50 and p, 8.95.

We can then proceed to calculate the overage and underage costs, right, for every shirt. For every shirt that I don't have that somebody wanted to buy, that's 2.45. And our overage cost, right, how much will each, for every shirt we order too high, 7.95. Our mean, mu, is 20,000, and our standard deviation is 1,000.

Critical fractile, just simply put it in the formula here, and you get 0.308 as the critical fractile. Go to a standard normal table, area of the cubic standard distribution, again use Norm.S.INV in Excel and calculate what z would be, and you get z to be -0.5. Plug z in here.

Your mean, standard deviation, and the answer you get is to order 19,500 T-shirts, all right? And if you think about that, that should conceptually make sense, right? Because the cost of having too many is way, way bigger than having too few, okay? Because the cost of having too many is way higher or fewer than the mean.

And in this case, it turns out you're gonna order 500 fewer. So it's pretty amazing actually and interesting to think about with just a few pieces of data, right? How much I buy this for, how much I sell it for, what my salvage cost is and what I know if I can generate a probability distribution for demand, even though I don't know demand exactly, if I can get an approximation of demand, with just those things.

I can come up with trying to balance the cost with having too much inventory with the cost of having too little and try to maximize my expected profit.

## Forecasting (Part 1)

>> Welcome to our first video lesson on forecasting. I've got three learning objectives really for this particular lesson. The first is I wanna discuss forecasting in the context of supply chain management. So bring it in how does forecasting apply to supply chain management? And if you'll remember, what we've talked about is one of the core things that a supply chain manager wants to do, is they want to take supply of the product or service and they wanna match it with demand, right?

And what's gonna turn out is that in supply chain management, the key thing that we're interested in trying to forecast is going to be demand. And so to help us with that, second learning objective is gonna be to discuss patterns of demand and talk a little bit about more about what demand looks like.

And then our third learning objective is I wanna talk about some different qualitative and really start to focus in on some qualitative, quantitative rather excuse me, quantitative methods in forecasting that companies use. So let me start with what is forecasting, right? And I've got a definition here forecasting is a prediction, right?

So that's a guess, usually an educated guess, but a prediction of future events. And then the key add on here is it's used for planning purposes, right? So what we're saying here is, we're trying to predict something that's gonna happen in the future, and then use that to help you plan now, right?

So a good analogy here is, you can think about it, is when you talk about the weatherman. When you get up in the morning and you go online to look at what the weather's gonna be. Or you get on TV to look at what the weather's gonna be, right?

The weatherman is predicting what the weather will be in the future and you use that to help you plan. Do I wear long pants, do I wear short pants, do I need to bring an umbrella, do I not need to bring an umbrella, right? It's the same in supply chain.

And in supply chain you will see that forecasting gets used actually for a lot of reasons. Its using strategic planning, so making a long term, do we need to expand and add another facility to produce? Finance and Accounting used for budgeting and cost control. You see it, marketing looking trying to predict future sales trend.

And then in productions operation management, short term by the way forecasting to try to determine staffing levels. So let's go into some general characteristics of forecasting. And I love this first one, right? The first one is a guess what forecasts are almost always wrong, right? Now, does it mean not usable, but are they gonna be 100% accurate every day?

No. And every time? No, right? All you got to again is look at the weather forecast, all right? And if you're like me, there's been countless days where the weather forecast says is gonnarain, and then there's no rain, right? Second thing is it forecast are more accurate when you aggregate or group together individual families of items.

So what I mean by that is, let's say for example, that you are a company that sells toothbrushes, right? If I'm trying to forecast or predict what domain will be in the future for a single yellow and blue toothbrush in Atlanta Georgia in particular and I'm trying to forecast demand for that, okay, is likely to not be accurate as the forecast or prediction of demand for all colored toothbrushes across the entire United States.

Next thing here is that forecasts are more accurate, the shorter the time horizon. And again if you look at the weather isn't weatherman as an example right, when the weatherman is trying to predict tomorrow's weather and forecast it, they tend to do better than predicting next week or predicting next month, right?

Fourth item is every forecast should include an error estimate. And then lastly, right keep in mind forecasts are no substitute for actual real demand data. So in order to predict a model demand, I think it's useful to touch on some common patterns of demand, and I've got five of them up here.

And in each of these graphs, what we've got on the y-axis is demand, And on the x-axis is time. And it's the same x and y-axis for each of these. And you'll notice, in this first one I've done here, each of these dots will represent, right, demand at a certain period of time.

And so on this first graph what we're seeing clearly as that as time increases as we go forward in time, what you should notice is that the demand is going up, right? As you go from point to point. So this is a trend of increasing demand, right? You may also see your data exhibit seasonality, right?

So periods of peaks followed by periods of low point. Peak, low, peak, low, peak, low, right? So product that has high demand in the winter may be low demand in the summer and likewise, right? There can be longer term, right? Like more cyclical elements. There can be was called autocorrelation which is where current data is influence by its own historical data, which I trying to kind to show here.

And then in some cases understand what demand there can be and there still will be pure random variation. And I gave you five different patterns that domain can exhibit and you get a course then in some cases, you can have multiple patterns appearing within the domain for certain products.

And so here is an example again showing demand or sales on the y axis, and time and years upon the x axis, you can see that not only does it appear to be seasonal variation, right? When you see this peaks here, peaks here, peaks here towards the start of each year, right?

But overall, demand is also showing a trend of increasing To continue with this whole premise that, you can and by the way will and do see different patterns of demand, right? I wanna bring in this notion of time series, okay? Cuz really what this graph is when you have a graph, right, of a variable versus time and you plot that, that's called a time series.

And I bring this up now cuz we're gonna come back to it, and we're gonna look at it extensively in some subsequent videos, right? But here, I'm just showing demand for whatever product I don't care what kind of product it is, but it's exhibiting just random behavior, right?

To me, random behavior is just that unavoidable, unexplainable, right, changes or fluctuations that occur in demand, right? If I had a trend to that demand it might look like this. So again, another time series with not only random behavior but then also a trend involved, right? And again I can go third way and adding seasonality.

And by the way notice here what I've done on this one is that we are showing here a time series that has seasonality and a trend. And by the way the trend is not what you wanna see with a company. The trend here is that demand is decreasing with time.

So, when it comes to developing a forecasting system or a forecasting model, right, it's useful to ask some questions about it, right? Starting with what's the purpose of what you're trying to forecast. Are you trying to forecast for capacity planning which we put in long term decisions? Are you trying to forecast for short term decisions, such as staffing levels, right?

You need to ask what kind of systems you're going to use or whether we'll use the forecast? Who is gonna use the forecast, right? And how important is it in predicting or how important is the past, excuse me, in predicting the future, right? And so answers to these, right, time horizons techniques level of detail will help you determine the best method to use.

And when it comes to the types of methods to use, there's two high level types of forecasting systems or methods. The first are things that are methods that are qualitative in nature, right? And that means that they rely on intuition or kind of opinion of one person or maybe experts.

So as an example, using Salesforce estimates, hey Salesforce, what do you think demand is gonna be for our flagship product next quarter, right? You're asking people ideally who are experts who should know your customers better than anyone else, what they think demand is going to be. But again, it's a subjective opinion, right?

So qualitative, right? The other type of methods are quantitative methods. By the way quantitative, the real word there quantity, right? So this are methods that rely on data, right? And rely on math and analytical techniques. And it's really where I'm gonna focus more on in this coming sessions.

And within the realm of quantitative forecasting methods, the three that you'll usually see practitioners or individuals as blockchain companies use are time series causal relationships and simulations, right? Time series are models that predict future demand based on past actual demand. And we're gonna see some graphs and we're gonna spend a lot of time there.

Because it turns out time series are the dominative methods that are quantitative and that are used for short time forecasting, right? Causal relationships are where instances where you have the data and you in essence you try to do maybe at least squares fit, you try to come up with an equation for a line that best fits that demand, hence hence linear regression, right?

And then more sophisticated models or simulations were if you're wanting to include randomness and some were non linear type of affects, right? So we've gone through now in a very high level, right, talked about what forecasting is, trying to predict future events. In the case of supply chain management it's about trying to predict demand for your product or service.

We've looked at some of the patterns that demand exhibits, right, from trends to seasonality or correlation, etc. We now understand that demand can exhibit many, if not all of these can exhibit all of these patterns. And then what we've seen is that companies, people, practitioners, supply chain experts will use a variety of methods and depending on what you're trying to forecast, etc., different methods or more useful, right?

And in that respect there is qualitative which by the way tend to be more long term type of forecasting method and then there are quantitative methods which tend to be used in more medium to short term. And so by short term I'm talking three months or less, right?

And now we're gonna do in the subsequent lessons is I wanna dive in to those time series methods in a lot more depth.

## Forecasting (Part 2)

>> So let's continue our discussion on forecasting. So in the last module or video lesson, right, we kind of laid some of the groundwork, talked about why supply chain managers are interested in trying to forecast. And in particular forecast demand so that they can help match supply of their product or service.

We talked about high-level or longer term qualitative methods, and more shorter term quantitative methods, right? Here I wanna dig in to one of those quantitative methods called time series forecasting, and start to talk about some of the different time series forecasting methods. And in particular here, bring out and discus or outline something called a simple moving average.

So we're talking about time series, I'm gonna start here and we're gonna start to develop and use some variables that I'm gonna try to stay consistent with as we go through all of this, right? And the idea behind a moving average model is it is going to use the last, and we're gonna identify variable here n to denote periods, in order to predict the demand in a time period.

And I'm gonna use the nomenclature here t plus 1. So t is gonna denote a time period, t plus 1 to me denotes today, t could be today plus 1 in the future, right? Cuz again, forecasting is about trying to predict the future. And when it comes to moving average models, there's two kinds.

There's what's called simple moving average, that we'll look at here, and then something called weighted moving average that we'll move to next, right? And the idea with both of these, right, is that they have this underlying assumption that the most accurate prediction for future demand is gonna be a combination of what happened in the past, what actually happened in the past.

So here's the actual, what's called the general form of the simple moving average equation. And I've got it for you right here. And this is called the general form. And so it may look like a lot, but what this is trying to say is that F, which is gonna denote forecast, the forecast in the next period, t plus 1, is going to be equal to A of t means actual demand in a given time period.

Plus actual demand A of t minus 1, is actual in the prior period, plus however many periods you're gonna have, divided by the number of periods. So let me give an example here. If I were trying to forecast, and let's say that my time period, by the way, is gonna be monthly buckets.

I'm gonna try to forecast the demand for March. It's gonna be equal to the actual demand, let's say for February, plus the actual demand for January, divided by two, right? That would be the specific form of this equation for a two period simple moving hours, right? So what this is saying is hey, my forecast for March is gonna be whatever demand was for February plus January, and divide by two.

Basically take the average. Let's see this in the context of an example, right? And so here's an example, and the question I pose here is, what is the forecast for week 13, which I don't have on here, right? So you understand there's no demand value given. But basically, if I had these same two here, what is the actual forecast, what do I predict demand will be for week 13 if I were using a four period simple moving average?

So what we're saying here is we wanna take the prior four periods of actual demand divided by four to get an average, and that's going to be our prediction, right, for the coming for the coming period. And so you see here, F of 13 equals, and this here is, again, the general form of the equation.

So this is for two period, three period, four period, ten period, twenty period, I don't care, okay? But this question asked us to do a four period simple moving average, okay? This becomes this specific equation for a four period simple moving average. And I've gone ahead and replace the t's, t minus 1's and so on with actual numbers, right?

So if you want to forecast period 13, with a four period simple moving average, this is the equation you use. And then it's simply a matter of plugging in value. So we come down here to the next line, F of 13 equals A 12, okay? This is A here, actual demand.

Week 12, A is 844, there you go, right? A 11 is 789, A 10 is 920, and A nine is 892. Add those up and, divide by 4, and you get, right, 861.25, right? So again, using a four period simple moving average, using historical data, right, actual demand data.

We're saying, hey, if we use this model, for pure simple moving average, we predict or forecast that in the next week, by the way, the time bucket here, the time bucket is weeks. In week 13, we forecast or predict demand is going to be 861.25. All right, so now you’ve seen your first time series forecasting model, okay?

Albeit the simplest of the ones we’re gonna look at, right, but hopefully, it starts to give you an idea, right, when you have actual data, right, you can begin to apply these methods. And in the next lesson we'll go ahead and we'll look at the next and the other, right, moving average, called the weighted moving average.

## Forecasting (Part 3)

>> Welcome again to our series on forecasting. In this lesson, I wanna look at something called a weighted moving average, show you what the equation looks like, and then give you a sample problem to see how it could be used. In a weighted moving average, this is what's called, again, what I'm giving you is what's called the general form of the equation right here.

Because as with a simple moving average, you can have a two period weighted moving average, three period, four period, five period. That's why you have the dot dot dot here. However many periods you wanna have, right? And the equation for a weighted moving average is the forecast in the next period, t+1, is equal to some weight times the actual demand in the given period plus a prior weight times the demand in the prior period, all the way up to however many you want.

And then there's another caveat, right? Which is simply that these weights, the sum of these weights, is going to add up to 1, right? So if you have a two-period weighted moving average, you will have two weights, w1 and w2, and they will add up to 1, okay?

Just like before, by the way, using the same nomenclature that we saw for simple moving average, t denotes current period, F is forecast, right, n is the number of periods, A is the actual demand, and w, again, is the weight. So let's look at using a weighted moving average again with an example.

And we're gonna use the same set of data that we saw for the simple moving average. So the same 12 weeks, the same actual demand values. And the question that's put here is forecast, come up with a forecast for Week 10, Using a three period weighted moving average with weights of 0.7, 0.2, and 0.1.

And so what I gave you here is, again, the general form of the equation can be for 1, for 2, 3, 5, 10, 20 periods, right? And what we'll do next is you wanna reduce it down to the specific form of the equation. In this case, reduce it down to a three period weighted moving average, with the forecast you're trying to do being Week 10, right?

So F of t + 1, you're trying to forecast Week 10. So if t+1 is 10, then t becomes 9, right, t-1 becomes 8, and so on. And then the weights 0.7, 0.2, 0.1. So a note on the weights. When you see the weights like this, the general convention is the first weight, and usually, the weight that has the highest value tends to be for the most recent demand, right?

So if you notice here in forecasting Week 10, 0.7, the highest weight of these, is being attached to the actual demand for Week 9. And then the next weight, 0.2, is getting attached to two periods out. And then 0.1, the smallest weight, three periods out at 0.7. Okay, now that we have the specific form of the equation, literally, it's just plugging in numbers.

So A9, actual demand for Week 9, there it is. Actual demand for Week 8, put it in. Actual demand for Week 7, plug it in. Multiply out and you get a predicted or forecasted value 861, right? And as a side note, that's a forecast. That would be a prediction, right?

And you can tell that the actual demand in Week 10 was 920. So quite a bit higher. So why do we need, or why do people like the weighted moving average models, and in many cases, like it more than a simple moving average, right? And the idea is because it gives you the ability to give more importance, again, to more recent data, right?

So as an example, if we took here January through June data, so we've got one, two, three, four, five, six months worth of data, okay? If I took indeed a six-month simple moving average, that's what SMA is, right, that would actually give me this value that's kind of in the light tan color.

However, if I did a six-month weighted moving average, Okay, and applied greater weight to June and progressively less to May, April as we go backward, you would see that it comes down lower and actually does a better job at trying to account for what, by the way, looks like a downward trend here, right?

So again, weighted moving average models give more importance to the more recent data. So one of the things I haven't addressed yet is how do we choose the weights? Are you ready for this? Turns out, right, cuz I gave you 0.7, 0.2, 0.1 were the weights that I just used in the prior example, how did I pick those, right?

How do I decide which are the optimal ones to use? And here is the answer folks, trial and error. You try some weights, you see what works best, right? Try some different weights, see if they work better, right? And what you ultimately pick is gonna depend on some things like how important we think maybe older data is versus newer data or newer data versus older data.

Do we have known seasonality, right? Those may help us in determining which weight I place more importance. And by the way, as a side note, and I've written it on here, you get, right, I've written it right here, you get that a simple moving average is really just a weighted moving average, with the weights for each period being the same, right?

A two period simple moving average has weights of 0.5 and 0.5. A three period simple moving average really has weights of a third, a third, and a third. Let me give you one other look at this, okay? And what I've done here is plotted, right, using some different weighted moving averages, as well as using a simple moving average.

And the point that I'm trying to show or to illustrate to you here is if you look, right, the red line denotes a weighted moving average, two period weighted moving average that's using 60 or 0.6 for the first weight, 0.4 for the next weight. And you see what it gives you here, right?

By the way, these simple moving averages you sense that they're all the same, it's 50/50. Right, oops, weighted moving average 70/30, right, starts to bring this down further. 80/20 brings it down further, right? So again, it's showing you, what I'm trying to show you here is that, right, that the higher you give the weight toward the more recent data, the more you will pick up the most recent trend.

So now we've looked at simple moving average and weighted moving average, right? In the next lesson, I wanna move into something that's used quite a bit in industry called exponential smoothing.

## Forecasting (Part 4)

>> Welcome back to our journey on forecasting. In this video lesson, our learning objective is to look at a another time series technique or model called exponential smoothing. An exponential smoothing is interesting in that what it does and by the way is different from the other two methods we looked at, is it makes the statement that hey, my prediction for the future is gonna depend basically and only on the most recent observation, the most recent actual demand.

And then, on how far off the most recent forecast was on the air from the most recent forecast. And we're gonna introduce something called a smoothing constant which will be denoted by alpha. This going to have the effect of determining how much we will change our prediction based on the air.

So why do companies like exponential smoothing? And by the way, if you were to buy a commercial forecasting software package, from the store today, and you actually were able to get into the code that that company used to develop that program, and you would look most likely you would see exponential smoothing in there somewhere at the core of that forecasting software, right.

And so there's a lot of reasons why companies and individuals like exponential smoothing as a method. For starters we're going to see is it doesn't use a lot of storage. Although I get it's not as much of a problem these days. But it doesn't require a ton of storage.

It tends to be very accurate, it's intuitive, easy to understand, and it doesn't have a very complex equation. As you're gonna see, there's not going to be a general form of the equation and a specific form. There's gonna be one form of the equation. So let's look at, that one form of the equation, for exponential smoothing.

And this is it, again, there is no general form of the equation, that is, the equation. And it says, hey, all right, our forecast for the next period is gonna be equal to whatever we forecasted last time plus our smoothing constant times this. Actual demand minus forecasted demand.

Now, by the way, if you think about it, what my demand actually was and what I predicted minus what I predicted it to be, the difference between those is basically telling me how far off was my forecast. If demand was 300 and I forecasted to 5300 minus 250 is 50, right?

I was off by 50. So again if if the actual demand was 300, and I forecasted, 50 and let's just say that A1, T1. Then if using this equation if i wanted to predict the demand for period two. It would be whatever the demand was for period one, plus this alpha times the difference between the two.

So what I predicted before plus some error term, all right? And alpha by the way is called the smoothing constant for exponential smoothing so smooth and constant. And as you might expect, it basically dictates, right how much the forecast how much the next forecast is gonna react to differences, right?

So this alpha value right here is low, say 0.1, right or even 0.01, then 0.01 times 50 is a small number, and you're not gonna see a lot of change in the new forecast, right. In contrast, if alpha were higher say alpha was 0.9, that's gonna make this term here, 0.9 times 50 is gonna make it 45.

So there's gonna be a lot of reaction to the differences right. So the picking of alpha, low alpha, basically smoothing out the air. High alpha is taking this air value here and applying most of it. Okay, the other piece of note here and I've got here is it alpha smoothing constant is a value between zero and one.

Hi, well, you know I wanna go next I wanna see this in an example, right? So here's another example. In this case, nine sets of nine weeks of data. And I wanna apply exponential smoothing, right? And again the general form of the equation if you want it back to see it again is F of T + 1 = F of T + alpha A of T minus F of T.

So there's the equation. If I wanted to forecast what demand would be in week 2, right? Equation simply is forecast for week 2 is the forecast that I use in week 1 + alpha, right? Actual demand on week 1 minus forecast week 1. So in these equations, we're going to set alpha equal 2.2.

We pick that will come to that in a second. But again, you just plug it in. 820 + 0.2 times A20 minus 8 minus A20. That second term cancels out. So again, forecast for week two becomes 820. If I wanted to go look at week four. I would have to have by the way, week three forecast.

Plug it in, and you get 785. Here's week six, same thing 757. I'll leave the math to you, if you wanna go through it. Week eight there it is. Week ten. Now, here's something to note. Notice how I have week ten forecast is equal to 760. And in order to get that week ten forecast, I had to know, I had to have the week nine forecast.

But in order to get the week nine forecast I had to have the week eight. To get eight I had to have the forecast for seven to get seven or so on. So what I'm saying is this method, unlike simple moving average and waiting, moving average with this method, wherever you start from, you've got to work progressively through all of the periods, all of the weeks in this case, to get to what you're actually trying to forecast.

Whereas if I was just trying to do a simple three period, right? Simple three period moving average I can do one equation take these three demands adamant divided by 3, and I'm done. All right, let's see this graphically. So let's plot exponential smoothing. So on here, blue one represents actual demand.

And again to see how a lower smoothing consent versus a higher smoothing consent impacts the results of this model, right. The red line denotes, a low value of alpha so you can see it's less responsive, one more stable. Whereas the green line shows what happens if we set alpha equal 2.8.

So a much higher smoothing constant, and as a result, right, much more responsive to changes in actual demand versus forecast and you as you can see. Much closer to mirroring the blue line. All right, so now we've gone through exponential smoothing again, right? A method that is pretty simple if you think about intuitively it makes a lot of sense, right?

My forecast for my next period is simply gonna be what did I predict this time plus some portion of how far off it was, right? So almost an adjustment and I'll put that adjustment with the current forecast and that'll be the next value that will go the next prediction that will make.

So now we've got three of the basic fundamental time series techniques. Simple moving average, weighted moving average, and exponential smoothing, okay? What we need one more piece here in forecast. And that's how do I look at, how can I evaluate how good these methods are? And that will be the subject of our next lesson.

## Forecasting (Part 5)

>> All right Bob Meyers back again to continue our discussion on forecasting and this lesson I want to get into the use of ever measurements and different era ballot use to use in helping a value way the accuracy of different saat time series methods and so when we're trying to compare or evaluate a given method or model so for example I want to value a 3 period simple moving average against a 5 period weighted moving average against exponential smoothing with Alpha equal to point to right the things that will want to look at or be aware of with respect to the error is you know does the method have a bias in it right meaning is there a consistent consistently over predicting or is it consistently under predicting demand right and then and so that I can separate that out from random errors that the model makes the just the did doesn't explain or doesn't seem to be able to account for it so best bias or randomness are the 2 things I'm kind of looking at evaluating and deciding if a method is good or bad to a kind of showed this when we did the lesson on exponential smoothing we saw all.

Of t. minus f. of t. in the equation and we ended up multiplying that by Alpha the smoothing constant Well now I want to go ahead and put a value put put put a variable to this and I want to call the actual demand minus to forecast the demand I want to call it the air and give it a variable e.

And by the way note that eat can be either positive or you can be negative right if the forecast if the forecast. Of t. turns out to be less then actual demand then this equation will be positive right. And what it's telling us is that we under predicted or under forecast what we thought demand was actually can be going to be on the flipside if our forecast for a given period turns out to be bigger then the actual demand then this equation here becomes negative right so a negative air indicates that we overall predicted or forecast demand All right well it turns out just as a measurement on its own is not particularly useful.

And so over the years people have come up with other a little bit more sophisticated methods for determine or types of error calculations and I've got a few of the more common ones here and the 1st is called r.s.s. feed which is simply the running sum of the forecast errors all this is is for each time period right so in week 9 What was the error week 10 What was the air week a level was there you add them up that's what this big this big sum Mason sign right here all that means is you some them all up.

And you get a running sum of the forecast here. I mention this one because it gets used in some of the other ones below here and the next next measurement we see used in many cases is called the mean forecast and by the way as I've noted on here this is a measure of bias mean forecast of the air so take your running some of your forecast errors that's all this one is you take your running summer and forecast errors and you divide to get a mean that's it.

Mean absolute deviation 3rd Mero measurement and looks almost identical to the mean forecast era but there's a there's a distinction here and we take the absolute value here that's the only difference. Take the absolute value why because I'm trying to get here a measurement of the magnitude of error rate recognizing sometimes demand can be higher I'm sorry forecasts can be higher than I predicted and in some cases forecasts can be below what I predicted right but what I want to get is a valid feel for overall right how far above or below actual demand do I end up being and that's mean absolute deviation 4th method is called the tracking signal and this again is going to be something to help us with bias.

And this is simply the running summer forecast errors divided by mean absolute deviation right let's take a look at this with some examples. Again I have a 10 period here Ok and I'm going to just do simple straight forecast of a 1000 for each of the periods right so my forecasting method is that there isn't any of the ones we've talked about it is going to be a 1000 every time I'm going to predict.

And each month I have a different outcome so you can see here in week or period one by the way period could be months I could even say month one right predicted a 1000. This is f. actual sales the way this is to write actual sales was 1200 so 1200 minus a 1000 is 200.

If I take the absolute value of that I get 200 as well let me switch down and go down to period 3. Again forecast a 1000 and keep keep it the same actual sales though it was 800 k. the error is 800 minus 1000 which is a negative 200 However the absolute value of the air is a positive 200.

Running some Come back over here running some of the forecast errors you add all of these up. To mean forecast error you take those same 10 errors that you calculated you add them up which by the way gives you that 200 and then you divide by how many you have you divide by 10 and you get right and m.s.p. of 20 mean absolute deviation is use the absolute value of the errors add those up 1600 divide them by how many you have 10 and you get 160 and let me touch a little bit more on the tracking signal right.

Because again tracking signal I said was kind of a measure of bias rate so it's a measure of how often another way to look at is how often are our prediction or forecasts is above what actual demand is well below it and in general the general convention is that if the tracking signal turns out to be less than 4 negative 4 rather or bigger than positive 4 that's a significant enough bias that you want to investigate or at least you want to say this model this method has some bias in it this enough that I'm not sure that I want to use it so just for completeness and that prior problem that we just looked at if we were to compute the tracking signal we would get a value of $1.00 which is within the realm of negative 4 plus 4 and so we would say Ok this thing is not too much to biased to out of whack in terms of considering that model is being usable.

So here's the thing we've got 3 time series methods we've looked at now simple moving average weighted moving average and exponential smoothing and we've discussed now a couple different measurement techniques right to use to evaluate a given model so now in our last and final lesson what I want to do is take all of this together now and use this is kind of a you know a bigger kind of problem a look at and say hey if I'm trying to implement forecasting you know how can I go about determining the best method to use.

## Forecasting Example Problem

>> All right, we're here, right? It's time to look at a sample forecasting problem. So what I wanna do here, again, is I wanna look at simple moving average, weighted moving average, exponential smoothing to try to come up with models of each of these. And then assess each of these three models using a variety of error values.

And of course, when I say assess them, I'm gonna be looking to you first to do the assessing and then together we'll talk about the results. So here's an example that I wanna look at. And again, like we've seen in some of the past lessons, please make sure to take the time to try to work through this first, before jumping to solutions.

And so in this example, what I've got is we're gonna say we've been hired as a consultant for Harry's Hardware. And they have some new special, awesome multipurpose hammer that's just the greatest thing ever. And they wanna try to do a better job of forecasting demand, why? Because they wanna make sure they have an adequate supply, because this is a very high margin item, and they wanna make sure they don't miss out on any potential sales to their competitors.

So what I want you to do, right, and by the way, I'm giving you here the last eight months or weeks, I don't care what it is, but the last eight periods of demand, of actual demand for this hammer. And so what I want you to do is, using a two period simple moving average, three period simple moving average, four period simple moving average, so that's three models right there.

Using two different weighted moving averages, and I've given different weights there. Using exponential smoothing with two different values for alpha. And by the way, forecast for period one being equal to 289. Why did I do that? Here's why I did that. Something else with exponential smoothing is, and when you go back and look at the equation, in order to get it started, you have to have initial forecast.

It's almost like a chicken and egg thing. How do I have an initial forecast if I haven't start, how do I have a forecast if I haven't started yet? So what you do with exponential smoothing is you have to, for the first period, you have to pick a value.

And I've picked a value F of 1 to be equal actually in this case to demand for period one. Anyway, so you've got three, four, five, six, seven different forecasting methods. Once you get to forecast periods one through eight using these methods, and by the way, in some cases, you cannot predict all of them, right?

As for example, a three period simple moving average, the first period you can actually forecast is going to be period four because you don't have enough historical data, right? In any case, for each of these methods, I want you to calculate, and this is the final, the deliverable, if you will, using these error methods.

Running sum of the forecast errors, mean forecast error, mean absolute deviation, and tracking signal. So what I'm looking for is I want you, and by the way, this is an exercise to go to an Excel, put the domain data I gave you on the prior side in slide in Excel, set it up in a table, however you wanna do it.

And then set up a two months simple moving average, three months, four months, etc. Set up all these methods, calculate the actual forecast, then calculate the error. And then calculate running sum of the forecast error, mean forecast error, mean absolute deviation, and tracking signal. And so the end result I want to see is something just like this what I have here on the screen right now.

So at this point, go ahead and pause, stop, whatever you wanna do. If you want, go back to the prior slide, look at those values, apply all of these techniques, and come up with these numbers. So go ahead and pause now. So I'm gonna assume now that you're done, you've got some answers, and so now we're gonna continue on to the next slide.

All right, and here are the answers hopefully that you got some of, or got all of, hopefully, right? And what I'm hoping that you did, right, cuz at the end of the day, making calculations and coming up with numbers is great. But the real value is in what is it telling us, how do we interpret this?

What can we do with this information we've got, right? So we've got here, again, these four error values for seven different methods, which, by the way, is interesting. Thinking about this for a second as well, we only had eight months of actual demand. But with just literally eight values, we were able to set up seven different models, and then come up with some measurements for all those models to evaluate how accurate or effective they were.

So what kinda thoughts did you have here, what insights did you see, right? And I guess what I'm saying is this game is a real good way, by the way, to do a bunch of what if scenarios, right? So one of the things you can do is say, okay, maybe what I wanna do is for each method, let me see which one did best.

So if I just look at running sum of forecast errors, which model seem to be best? And I guess the argument could be made this one here actually has the smallest value overall. And by the way, it's negative, right, and negative denotes that our forecast was bigger than our demand.

If my goal is to never run out, right, I wanna make sure I always have as much or more than demand. So that would seem to be four months simple moving average, on that measurement alone, seem to do best. If I look at the mean forecast of the error, two months simple moving average did best.

But I'll give a honorary mention to exponential smoothing and I guess maybe four months simple moving average. Those three were pretty low and the others were in the eights, all right? Mean absolute deviation, best value, smallest is that one, four months simple moving average, honorable mention to exponential smoothing with an alpha of 0.2.

And then tracking signal, I mean, you could argue and say, okay, well, this one have the smallest tracking signal. I would note that this one gives me caution cuz it's getting closer to four. It's not quite four yet, but it's getting towards the upper bound. Now, by the way, what I also give you here is, right, one of the things you can also run into with forecasting is, is there really a method that sticks out and is dominant to me above all the others?

Well, I can say at least, by the way from doing this, that I'm not sure I'm too interested in weighted moving average. It didn't seem to perform well at all, so you can probably get rid of it. And for whatever reason, it turns out that a three month simple moving average wasn't entirely enticing, all right?

But the others, there isn't a clear dominant winner, which is another set of issues and for another time in terms of how I get down to which specific model I want to. And the answer is, by the way, that end up being some things like it may be that you take an average of models, or you do a challenge or champion thing.

You take a model and you say, I'm gonna use this model for next period, and then I'm gonna go back and recalculate. Whichever one's best, I'll use that model for the next period and so on, okay? So a lot of choices, and yes, I'm telling you, companies do do these kinda things, all right?

All right, again, and I said it before but I wanna say it one more time. It's amazing that literally with just eight values, eight single values for eight time periods, we were able to very quickly, and very easily within Microsoft Excel, generate seven different models. We could have done more, right?

And then evaluate those models. And by the way, if you were thinking even farther ahead, you probably started, in your head, hopefully were thinking, you know what? I could probably even go a step further in Excel and use that thing called solver to give me the optimal value for alpha or to give me the optimal weights to use.

And the answer is yes, you could, right? So again, putting all this together, it's amazing to me, the quantity and the insights in the models that one can develop. And that's gonna conclude our lesson on forecasting.

## Trends

>> Welcome to our supply chain video on some technology trends that I think are very exciting, very promising, and to me, have the potential to radically disrupt how supply chain is done and handled in the future. And so what I wanna do in this lesson is I wanna look at four, in particular, four technologies that, again, I think can radically, fundamentally change how companies try to match up their supply product with the demand for it.

And the first technology is 3D printing. I'm sure you've heard of it, I'm sure you may have even seen some examples of 3D printed projects or products. And here's the thing for me about 3D printing. It's, to me, eerily similar to paper printers. And so if any of you are old enough or as old man like I am, all right, now, when paper printers first came out, some of the early ones were something called a daisy wheel.

And so literally it had all of the letters and numbers of the alphabet around a circle, circular wheel. And what it literally would do is it would turn to the letter you wanted, and then there was a hammer behind it, in a ribbon in front of it, and the hammer would strike in that letter.

Which was raised out on the wheel, would be stamped against the ink, and it would put that letter on the piece of paper. And then it literally would shift the paper over slightly, rotate around to the next letter stamp, shift the paper over, rotate to the next letter stamp, right?

And by the way, it did it with one color, right? So it was one color, it was slow, by the way. There were no multiple fonts, none of this stuff. You had a single font which was on the wheel, okay? And when I say slow, it could take several minutes to do one page, right?

And you look at paper printers of today, right, you get multiple color that comes out of those printers. In fact, you get photo quality at a lot of these printers these days right? They are much better resolution, right, they are multiple colors. And some of these laser printers today, they just stream off the pages.

So what I'm getting at is that technology has advanced so much in time that the more limiting aspects of paper printers have certainly changed and got a lot better. So I take that and I say, hey, to me, I see a similar thing happening with 3D printing, right?

3D printers today, if you notice in the pictures here, they print in a single color. Now, you at least have multiple colors, but it's a single color. And it's the color of the filament, if it's an additive type printer, right? The resolution, by the way, and you can see on this picture, you can see the grains, the resolution is not that great, it's not that crisp.

It's not terrible, but it could be a lot better, right? And the printers in general are pretty slow, you can take 10, 12, 20 hours to produce one of these things, right? But think about in the future, what happens with 3D printing and the use of 3D printing in terms of supplying and meeting demand for your product.

What happens when now all of sudden, you can do multiple colors? And by the way, there’s some printers already starting to do that. And not only can you do multiple colors with 3D printing, but what happens when you can use multiple materials? That’s an interesting one. What about when we get to the point where you can use metal and plastic, and maybe even wood, right, and concrete, whatever it is, multiple different materials of different colors in the same print?

And what about when the resolution gets much better and you don't see the graining anymore? And what about when it doesn't take 10 to 12 hours to produce a single product, right? Can you imagine now, and maybe I'm just thinking out loud, but when you get to that point, right?

There's something already that comes to mind to me, which is the notion we've talked about way earlier in one of our sessions, which is postponement. Could we reach a point where retailers don't have the final products? Literally, think about this, retailers don't have the final product sitting on the shelves in a box for you to pick up and buy.

You can go in, or maybe you don't even go in, but you go in, let's say, at some point maybe and you see a product and you go, I like that product. And as you're walking up front, that product is literally being printed, all right? Think about how that changes how companies meet demand.

And it changes it in a very radical way, right? The potential is here, we'll see if it happens. Another, I think, big technology trend, artificial intelligence, all right? The whole notion that using, and by the way, almost everything under the umbrella now seems to be using data. Almost every company is trying to use data to help them make automated decisions, right?

And in particular within the realm of this, and it gets used a lot of ways, I think about something called predictive analytics, right? So it's using historical data to try to predict, in many cases, failure or predict something is going to happen. Sounds kinda a little bit like forecasting, right?

And in a sense, it is a method of forecasting. But companies are harnessing the data, in particular jet engine makers. So the jet engines that you see on Delta Airlines, or Southwest, or whoever it is, right, GE, Rolls Royce. What they all do now is they are collecting all hordes of data from their actual engines installed on Delta, Southwest, and others.

And they're taking that data and crunching those numbers to try to look at if, for example, a plane has an engine problem one day. They'll go back, when that plane has an engine problem, they'll go back and start to comb through the data. Or rather yet, they'll have programs and artificial intelligence combing through that data, trying to see, hey, do I notice something that looked at a whack just prior to the engine failing or having a problem?

And then they'll start to use that then and they'll say, okay, now, in the future, when we start to see those precursor conditions starting to appear in another engine, that's gonna be our note that hey, it's about to have an issue. And we'll go ahead and proactively have that airplane brought in and that engine replaced, they're plug and play, by the way, take one off, put another one on.

So maintenance, whatever can be done to this engine prior to it failing. So again, by the way, automating decisions, using predictive analytics, better information, faster decisions, right, shorter lead times, and shorter lead times better able to match supply with demand. Another biggie to me, the third one is robotics.

And in particular, using robotics, here I'm talking about using robots to automate manual tasks, right? Amazon, right, one of the largest online retailers in the world, has small, little, round, almost like discs, look like hockey pucks almost, called Kiva robots. That now, through some of their warehouses, right, go through and they literally, what they do is they go underneath a container full of products.

They raise up that container and they bring the container back up front of the warehouse to a person who then picks products out, they're an order picker, they pick the products out, right? That, by the way, has replaced a traditional order picker. They would get an alert, so when you make an order on Amazon, they get a list, and they'll call it a pick list, of all the items that you've ordered.

And they will then begin to walk through the warehouse to pick the items up, the individual person will, right? Now, again, what Amazon's doing, though, is they've changed that game to where a robot is literally picking the container of products up and bringing it up to the person.

So the person now is stationary. And by the way, it's led to a lot of other things, like they no longer have to keep items, all the same item in the same place. They can have more of a dynamic inventory, where there's different products on these different containers.

And they can get a whole lot, by the way, more done in a given period of time. And they can get these things picked and sorted faster, so they can get closer to that, quote, same day delivery type model for online purposes, or purchases rather, right? And so now, what I think you'll see next, and by the way, what we are seeing already is robots now getting good enough.

And by the way, artificial intelligence plays a part here too, but getting to the point where they can start to do the order picking as well, the part that the human is still doing, right? By the way, we're seeing robotics in a lot of other areas as well.

We're seeing robots used to make food, right, literally, flip hamburgers, I'm not kidding, make bacon eggs, whatever it is, right, robots to do that. If you go into a lot of car assembly plants today, you will see extensive use, in almost every case, of robots to weld the car frame together, to stamp and press the roof, and the hood, and the trunk.

And again, you get more uniform quality here, right, faster, shorter lead time, all those things again, all right. Fourth one, again, I think, and you look at all these, you gotta be like, my gosh, we got change coming, is autonomous vehicles. And in this case, autonomous transportation vehicles, right, driverless tractor trailers or driverless ocean freight carriers, right?

You've seen those big, massive ocean, I mean, literally football fields long, ocean, right, carriers that have literally thousands of 40 foot, 20 foot rectangular containers on the back of them, okay? I'm just telling you, the big ocean companies of the world, right, the Mares, the CMA CGMs, they are looking and working on trying to find ways to make the boats driverless, automated, right?

Trucking companies looking at ways to make the trucks automated, right? Why does this benefit me? Well, at least in the trucking industry, there's rules around how many hours a driver can go before they have to stop and rest, right? Driverless vehicle doesn't have that, they just have to stop to refuel, all right, or perhaps have maintenance.

So by the way, do you see some similarities? With all four of these, and I kinda touched on it, but what's interesting to me is all four of these ultimately are generating huge amounts of data. Or they are using huge amounts of data and making a lot of calculations, certainly robotics, actually all of these are, right, a lot of calculations, a lot of data, right?

And since that underlies them, you get that they're going to have a need, and there's going to be a need for analytics, right? So I think driving a lot of these things, right, fundamentally, radically changing how companies do business is going to be the need for analytics. I just scratched the surface, folks, right?

I mean, just with these four alone, can you imagine, right? Autonomous vehicles are in existence and in use regularly, trucks, boats, right? Robotics heavily use, right, artificial intelligence in use, 3D printing, right? Faster, better quality, multiple materials, multiple colors. Can you imagine, when all that comes into play, and those may be different when those technologies mature, how much different operation supply chain will be from what it is currently today?

## Wrap-up

>> All right, so we're at that point in time where we're gonna kind of wrap up all we've been looking at here. And by the way, we've looked at a lot and hopefully as you felt for me, I think this is an incredible time to be involved in operation supply chain management.

We're on the cusp I think of some radical fundamental amazing changes, all right. But just the kind of recap where we've gone through in this last several sessions, right? We start about by saying, hey, you know, here's how we can kind look at operations and supply chain management.

You can look at in terms of a set of decisions, right? Or as report here, developing capabilities. So, decisions around which capabilities you're going to develop. And those capabilities to designing, producing and delivering products and services in a competitive market. So we started there and then we said hey, further this we can look at those decisions or developing capabilities.

How you wanna put it is being long term, medium term and short term and this will kind of lay the framework for how will go. And so we spend some time going through here long term decisions such as, right, in addition or in addition to why operations supply chain management is important.

We looked at, hey, what's the difference between an efficient and a responsive supply chain? What kind of operating model there and should you look at? What kind of network configuration do you wanna have? To what degree do you want to outsource or offshore, your products or services? And then if you wanna cut kind of medium term decisions in terms of timeframe, we looked at lean operations a little bit, I wanted to give you a prep and then look into the lean operations.

We talked about service and operations, planning RSOP. And then we ended that error of that particular section looking at some just basic inventory management models, right? So how much to order, and when to order more, making a lot of simplified assumptions, but again, just the basic model, all right?

And then we moved into looking at some of the more well known supply chain concepts such as the bullwhip effect and the newsvendor model, two classic ones, right? From there we went into forecasting cuz again we said hey, you know, really at the end of the day, supply chain is about matching supply of your product which I've had over here to demand for your product, right?

And one way to help you better match get supply right is you got to make a prediction cuz this thing demand changes with time. But if I can predict it, or forecast it, and the better I can do that, then the more likely I may be able to make the right kind of decisions, planning decisions to match my supply with demand.

And we looked at several time series models, which are typically using fork and short term forecasting, right? And then we kind of wrapped up and said, I'm telling you this, this is an incredible time. And I just gave you for technology Tango, these four technologies, right? I mean, these are really gonna help and change a lot how a lot of the other decisions are made and how companies operate?

And what kind of is interesting then with all that, is that data, cuz there will be a lot more of it coming, in analytics, I firmly believe will play a key role in the supply chain of the future, right? Cuz again, most of those new technologies we rely upon.

I hope you're excited as I am about this stuff. I think it's amazing, incredible, awesome and I can't wait to see how things evolve. Thanks for your time.