Why cohort analysis beats all other approaches to calculating LTV

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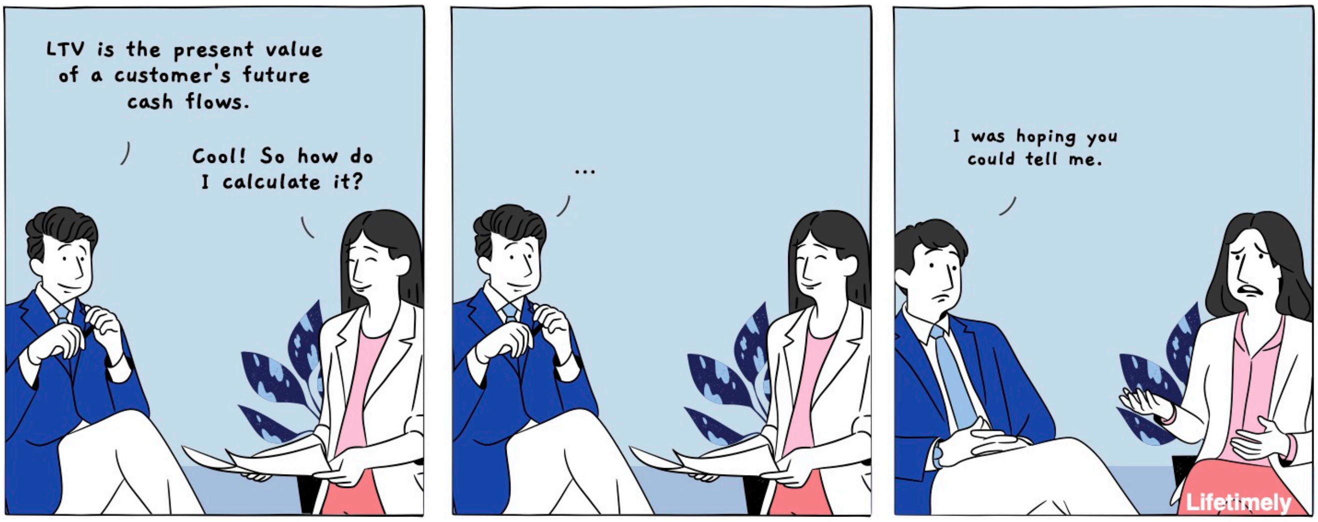

Sooner or later, anyone involved in e-commerce will come across the concept of customer lifetime value (or LTV for short). LTV attempts to answer a seemingly straightforward question: “How much is an average customer worth to my business long-term?”

There are plenty of reasons why this is a great question to ask:

- It shifts focus from profit margins on first orders to accumulated profits over a lifetime of orders - a much better metric of customer value.
- It encourages customer retention efforts.
- It allows for more sophisticated customer acquisition strategies.

But there’s a catch. **By its strict definition, lifetime value is impossible to measure.** For a by-the-book calculation, you’d need to know the precise date and value of all future transactions - something no business could hope to achieve. And while plenty of workarounds have been developed that claim to produce accurate LTV estimates, **nearly all of these approaches would be dismissed if presented in a meeting with a venture capitalist**. In fact, the only LTV metrics most VCs look for don't match the strict definition of lifetime value, and the main questions they want answered don't match with the question above.

So what is it they're looking for?

Most VCs are only interested in the range of LTV metrics produced by cohort analysis. **Compared to other approaches, cohort analysis provides by far the best framework for estimating LTVs that you can leverage to make more profitable decisions for your business.** Even if you're not trying to raise VC money, learning how to apply it can inform nearly all your most important business decisions and provide a major competitive advantage.

But before we dive into why it works and build a roadmap for how and when to apply it in your business, let's first dissect why nearly all other approaches fall short.

How most methods of LTV calculation are flawed

What makes for a useful metric? Basically, you want data that's:

1. **Actionable** enough that there are multiple meaningful business decisions that it informs
2. **Reliable** enough for you to make those decisions with confidence

A surprising number of LTV approaches fail on both counts.

A good example is the approach advocated on Shopify's own blog. Shopify applies a very common equation-based method of estimating LTVs. Their formula is simple - since LTV is the total amount a customer spends (or nets) with your business, average LTV is the product of the following three numbers:

- Average order value (How much an average customer spends on an order)
- Average purchase frequency (How often an average customer orders)
- Average customer lifespan (How long an average customer continues to order from the business)

LTV = Average order value x purchase frequency x lifespan *(Nice in theory, not so nice in practice!)*

So let's say the value of an average order is $50, an average customer orders from your store twice a year, and you expect a customer to stick around an average of five years. What would be your business's average customer LTV?

Multiplying across gives you $50/order x 2 orders/year x 5 years/lifetime = $500/lifetime.

Simple enough! But does it hold up to our standards of actionability and reliability?

Are metrics reliable?

In theory, there's nothing wrong with the logic here. But the effectiveness of the equation relies entirely on our ability to accurately estimate the three variables in the equation. Is that feasible?

For average order value and purchase frequency, we can base our estimates on past customer behavior. But what about lifespan? Do we know how long past customers have stuck around on average?

If you run a contractual business, where customers have a relationship with your business for a set period of time or until they notify you otherwise, an estimated lifespan is tricky, but not impossible. If you track your churn rates and those churn rates have held stable over time, you could extrapolate an average lifespan from those figures. (You still wouldn't want to rely on this equation over other LTV methods, but we'll tackle subscription businesses in a separate blog post).

But what about non-contractual businesses? With no contract, you never know when or if you can expect a customer to place another order. There's no clear line between active and inactive customers, since every customer you assumed was inactive can surprise you with an order, and even your most active customer may have already made their last order without you knowing.

So how can you estimate an average lifespan without knowing which of your customers' lifespans are complete and which are ongoing?

Very few advocates of this equation approach to LTV calculation offer any real solutions to this dilemma. Some say to look at precedents in your industry. Shopify simply says to use 3 years as a stand-in if you're not sure - an arbitrary number that makes no allowance for variations between businesses.

With enough sales history, you may be able to find some some clues in your data. But in the end, how much could you really reduce the potential error margin here? Could you say with certainty that your estimates are within 20% of the actual number? Or even 50%?

And to circle back to our litmus test - would you have enough confidence in an estimate produced by this equation that you would use it to make important decisions in your business? Probably not. Of course, any other approach that asks for uncertain estimates at the outset fails this test as well.

Are metrics actionable?

Let's imagine that we were somehow able to have perfect faith that we'd calculated our average LTV exactly, either by the equation above or an equivalent approach. If that were the case, how could we use it to our advantage? Would it help with the most common uses of LTV, such as determining how much to spend in customer acquisition, anticipating future cashflows, or discovering which factors drive your highest value customers?

In terms of the first two, even if we know what the average spend will be over the next five years, we don't know how or when we'll receive that return. Can we expect most of that value to be delivered in the first year after a customer's first order and then quickly taper off? Or do customers tend to purchase discounted products initially and then gradually order higher value items? **Unless we get a sense for how customer value is distributed across a lifetime (known as "sales velocity"), we can't estimate future cash flows, nor can we estimate when we're likely to break even on customer acquisition costs (CACs)**. For businesses that don't have unlimited cash on hand, this is an issue.

Knowing only the average LTV also fails to give us any insight into what motivates our top customers to spend so much. If we receive 10 orders in an average lifespan, then that average must be buoyed by a minority of customers who are ordering much more frequently (to account for all the customers who only ever place one order). Do these customers have anything in common? Were they won over by the same marketing campaign? Are they drawn to a specific product? If all we have is a composite figure, we can't investigate what's working and what isn't and then act accordingly.

What would we need to improve on this approach?

Ultimately, "What's my average LTV?" is the wrong question to ask. Some better questions to ask would be:

- **"What's an average customer worth to me 3 months after their first order? What about 6 months, 9 months, 12 months, and 24 months?"** Knowing the rate at which customer value is distributed would help us anticipate returns on our CACs and month-to-month cash flows, which would in turn help us decide how much to spend to acquire new customers and how to manage your budget over the coming months.
- **"How does an average customer from a year ago compare to a more recent customer in their accumulated sales after 3 months, 6 months, etc?"** This would factor in potential differences in customer behavior over time.
- **"How do my LTVs compare across sales channels? What about product types, countries, or sales campaigns?"** LTV could become the measure of the effectiveness of each of our business efforts to help us double down on what works and abandon what doesn't.

The lesson here is that the more we can segment our customers based on shared characteristics *before* calculating LTV, the more actionable our data becomes. In the context of calculating LTVs, simplicity is not an asset. We need a more nuanced approach - one that captures LTV velocity, accounts for customer heterogeneity, and provides a systematic framework for comparing LTV across customers with different attributes.

And of course, we need an approach with reliably accurate figures. This means relying on historical data, since we run into trouble when we're asked to come up with projections of future behavior.

Only one method of calculating LTV matches on all this criteria - the cohort analysis approach. Let's break down what it is, why it scores so high on reliability and actionability, how you can get more sophisticated with it, and how it can be a difference maker through different stages of your Shopify store's growth.

Simple cohort analysis - how it works and what it can do

Cohort analysis is an attempt to extract actionable insights from historical order data by segmenting a customer base into "cohorts" and then measuring each cohort's behavior over time. This helps you isolate the effect of different variables of customer behavior.

Cohort analysis can be applied in different ways. In the context of calculating customer LTVs, customers are segmented based on the date of their first order with a business and tracked on a metric (usually average sales or average gross margin per customer) that measures how much an average customer from that cohort is worth to your business over time. Instead of ending up with one average LTV, you get a matrix of LTV "snapshots" of each cohort's LTV averages based on how long it's been since those first orders.

Let's look at an example. Below is a simple cohort analysis created in Excel. (In a later post, we'll walk through how to run this analysis on your own.)

			Months sice first order					
First order at	New customers	First Order	0	1	2	3	4	5
Jan-2021	3587	$57.70	$61.10	$67.30	$74.60	$78.70	$82.50	$83.30
Feb-2021	2477	$60.30	$63.40	$72.00	$77.70	$82.50	$83.80	
Mar-2021	2295	$68.10	$73.40	$80.30	$87.90	$89.60		
Apr-2021	1890	$69.50	$72.30	$80.00	$81.60			
May-2021	2075	$63.80	$67.10	$68.60				
Jun-2021	2893	$57.80	$58.00					

This report was generated from six months of Shopify data. Cohorts are organized by the month of a customer's first order, and as you can see in the first column, each cohort is given its own row. The second column tells you the number of customers in each cohort.

From here, we start to calculate how much an average customer in each cohort is worth to your business at different points in time. We're measuring customer value here as the average accumulated sales per customer in each cohort. In other words, we're taking the total sales made by all customers in each cohort and dividing by the number of customers in each cohort.

Let's focus on the Jan-2021 cohort. The average value of a first order was $57.70. Of course, to measure a customer's total value, we need to track all orders - not just first orders. So column 4 ("0 months since first order") shows you Jan-2021's average customer value with all of January's sales factored in, including repurchases. Column 5 shows average value when you factor in all January

months passing from their first orders to the present day.

Now we have our basic framework. And even if we had tracked along a longer or shorter time frame, grouped our cohorts by a different rule, or measured LTV with another metric, the framework would look essentially the same.

Before we add more layers, let's check in to see how we're doing on reliability and actionability so far.

Are metrics reliable?

The first thing to note is that with basic cohort analysis, we're not making any assumptions about the future. The focus is on analyzing historical order data at different levels of detail to learn as much as we can about the behavior of our past and current customers. All of this data is verifiably accurate. Though there are some caveats with basing business decisions solely on past customer behavior (which we'll get to later), this is far preferable to relying on future-focused metrics with potentially high margins of error.

Are metrics actionable?

Now that we're tracking sales velocity, our LTV data becomes much more useful. Using Jan-21 cohort as an example, we can see when the majority of repurchases were made and when total cohort sales start to plateau. And if we know the costs associated with this cohort, this means we can determine how long it took to break even on customer acquisition costs and on total costs.

Comparing with other cohorts can help us decide if January was an outlier cohort, how new customers compare to older customers, and whether there are any noticeable trends over time in your short and long-term LTVs over time.

Together, all these factors inform how much to spend to acquire new customers based on when you can expect to break even on those costs and how much you expect to make beyond that breakeven point. You're also in a much better position to forecast sales from each cohort month-to-month.

What would we need to improve on this approach?

Basic cohort analysis gives us insight into how our customer base has acted over time. In other words, it explains the what of customer behavior. Where it's limited is in explaining the why. We see that there's a lot of LTV variation both within and between each cohort, but we don't have many clues as to what drives those differences.

So the next challenge is: how do we go deeper to identify our most profitable customers and find patterns that explain what motivates them to spend more?

The key to customer centricity - cohort analysis across different customer segments

All we need is one more layer. Instead of doing cohort analysis on our entire customer base, we create separate matrices for our customers based on a new variable. This could be any customer behavior metric - marketing channel source, first product purchased, country of origin, promo code, etc. When we run separate reports based on differences in this new variable, we essentially isolate its effect. That effect can be measured by focusing on the differences between each matrix.

Here's an example. The reports below are from the same data set as above. Isolating variables is a bit trickier to do in Excel, so to make it easier we'll just use the filters option in Lifetimely. We'll also switch our metric to accumulated gross margin per customer to incorporate our cost data and focus on profit instead of revenue.

We have two LTV reports here. The top report is for customers whose first order was Product A, and the bottom Product B. The CAC is equivalent for both groups of customers.

First order: Product A

					Months since first order					
First order at	New customers	*CAC	R-%	First Order	0	1	2	3	4	5
Jan-2021	3587	$7	22%	$31	$33	$36	$40	$42	$44	$45
Feb-2021	2477	$6	23%	$33	$34	$38	$41	$44	$45	
Mar-2021	2295	$6	22%	$36	$38	$42	$46	$47		
Apr-2021	1890	$6	16%	$38	$39	$44	$45			
May-2021	2075	$5	7%	$36	$38	$38				
Jun-2021	2893	$4	0%	$32	$32					
			Average	$34	$35	$39	$43	$44	$44	$45

First order: Product B

					Months since first order					
First order at	New customers	*CAC	R-%	First Order	0	1	2	3	4	5
Jan-2021	1532	-	26%	$37	$40	$44	$48	$51	$53	$54
Feb-2021	1262	-	25%	$38	$39	$44	$47	$50	$51	
Mar-2021	1214	-	24%	$42	$45	$49	$54	$56		
Apr-2021	1053	-	16%	$43	$45	$49	$50			
May-2021	1229	-	7%	$39	$41	$41				
Jun-2021	2007	-	0%	$35	$36					
			Average	$39	$40	$45	$50	$52	$52	$54

Let's compare a few data points here. Not only is Product B more profitable on initial orders ($39 average gross margin on first orders vs $34), but that margin is increased from month-to-month. After 3 months, average accumulated gross margin is $52 for Product B vs $44 for Product A. Sales then seem to mostly plateau beyond 3 months.

This suggests that when Product B is purchased first, customers return a higher profit in both the short and long-term. (To test this theory, it would be wise to run the report again with adjusted timeframes to see if the trend holds over time.)

This of course doesn't mean you should drop Product A from your product line. Both products are profitable, return CAC very quickly, and lead to relatively strong repurchase percentages.

But what this tells you is that when it comes to resource allocation, it's more likely that you'll see a greater return on investment if you focus your resources more on Product B. This could mean featuring Product B on more advertisements, offering first-time promo codes on Product B, promoting it to existing customers who purchased another item first, developing new products that are similar to Product B, or all of the above.

Of course, none of these efforts are guaranteed to increase the average LTVs of present and future customers. To confirm that they're having an effect, you'll want to continue to track LTVs month-to-month, isolate different variables, and gauge whether your actions result in higher-value customers.

When you repeat this analysis with different marketing campaigns, sales channels, product types, coupon codes, etc, you'll get more and more actionable feedback on who your high-LTV customers are, how best to keep them engaged, and how to acquire more customers like them.

This creates a virtuous cycle known as customer centricity, where you use LTV as beacon to help you adapt your business to build a more profitable customer base. And the more thoroughly you embrace cohort analysis as your primary method for tracking your metrics and comparing them over time across customers with different attributes, the better you'll be able to make businesses decisions with higher ROI in the short-term and the long-term.

Caveats of cohort analysis

As we said earlier, no LTV approach is without its shortcomings. Here are some things to be aware of:

- **It's challenging to do on your own in Excel/Google Sheets**. This is especially true if you want to incorporate cost data and if you want to update your data regularly as sales come in. As your business gets more sophisticated and your customer base grows, you'll most likely have to turn to third-party apps to do this for you.
- **There's a learning curve.** Whether you choose to do your own cohort analysis or find someone to do it for you, it may take some time to learn how to interpret your data, how to manipulate it based on what you're hoping to learn, and then how to

leverage it to make better business decisions. The payoff is there, but proper analysis requires some dedicated practice.

- **Historical data can only take you so far.** In the e-commerce world, there's always the possibility that new customers might behave very differently from the patterns established by your existing customers. These differences may be especially pronounced when you experiment with new product offerings or marketing efforts. But because cohort analysis requires collecting multiple data points over time, it's difficult to arrive at any significant conclusions about your latest customers. So while historical data is a crucial starting point and is certainly enough to help you make more informed decisions (especially in the short-term), it's important to keep aware of the possibility of unexpected customer behavior.

A quick word on predictive modeling

When new customers start behaving in unprecedented ways, this doesn't necessarily make your historical data obsolete. As LTV analysis becomes more sophisticated, many companies have developed predictive models that dig for nuanced patterns in past customer behavior to come up with projections for how your newest customers are likely to act over time.

These models can be especially useful for companies in competitive industries who already have long order histories that these models can learn from.

But of course, any projection of the future carries a potential error margin. Even if the model produces projections much more reliable than a human could, no model will be completely foolproof. Anyone interested in adapting one of these models for their own business will likely want to do some research into how rigorously different models have been developed before selecting one.

A roadmap for when and how to calculate your LTVs with cohort analysis

Let’s circle back to deciding how cohort analysis can benefit you based on the current state of your business.

Stage 1: If you’re just starting out, it’s probably a little early to try to calculate or anticipate even your short-term LTVs, since cohort analysis requires a base of historical data to be valuable. But it’s great to have it on your radar and to anticipate using it in a customer-centric way!

Stage 2: Once you've developed some sales history, perhaps after a year, then cohort analysis starts to become more useful. If you know your pivot tables and want to give it a go yourself in Excel, then go for it!

Stage 3: If/once you have a more extensive product list and/or order history, third party apps make sense for most stores from the standpoint of time-savings and added functionality like different metrics and the ability to isolate multiple variables of customer behavior.

Stage 4: Predictive modeling is a feature that you can always grow into. Generally the more sales history you have, the more accurate a predictive model's projections will be.

And remember - it's best to always try to keep the bigger picture in mind. As helpful as LTV can be for your business, it shouldn't become a singular target. Remember Goodhart's law: "When a measure becomes a target, it ceases to be a good measure." In fact, it's a natural progression to have overall LTV decrease with time. And that's ok - if you continue to attract and keep enough high-LTV customers, profits should still grow even if high numbers of lower-LTV customers bring down your average.

A good metric should be a tool to help you make better decisions. Together, your metrics should support a never-ending process of digging into your data and trying to make improvements to serve your customers more effectively. Cohort analysis simply helps you navigate this process with the best metrics possible.