Predicting lifetime value

How adopting customer lifetime value strategies leads to profitable growth

Meta

Foreword

What actions would you take today if you knew the future value of new customers? If you could see today which ones are going to bloom late, and which are going to leave your business after the initial purchase, would you change your customer acquisition efforts? Would you reassign limited financial resources to channels that better reflect long-term value? These are questions every business leader should consider and the tantalising possibilities explored within this paper.

Customer insight is an essential way for a business to stay competitive. It helps companies not only concentrate on delivering exceptional customer experiences but also on acquiring the right customers. The Pareto Principle points out that 80% of a company's revenue is generated by 20% of its customers. These customers are the 'vital few' who are loyal to your business and spend more than the cost to acquire them. In pretty much any category you can think of, competition is fierce for the 'vital few.' We all compete in a changing environment where consumers have more choices than ever. Your company's competition has most likely increased in number and size, so too has an abundance and complexity of communication touchpoints.

In this competitive milieu, when customer insight can be the differentiator between success or failure, poor measurement can let us down. It's still common for marketers across the globe to base business decisions on last-click attribution models. Not only do those models misattribute the value driven by channels, confusing how customers discover your products, but their popularity also highlights a strong focus on the 'here and now' of short-term revenue driven by customer acquisition campaigns. But shouldn't a business keep its best customers for longer than just a moment?

True, the importance of calculating customer lifetime value is nothing new. It has been in the centre of the decision-making processes for many businesses for some 50 years where it's been the guiding star to secure profitable growth in the long-term. And in times of economic uncertainty with pressure to 'do more with less,' businesses are rightly focused on profitability rather than pure revenue growth. But being able to accurately predict and act on customers' lifetime value are key elements that have been missing so far.

The development of machine learning computation puts prediction within reach for those businesses with the right skill set or those working with the right partners. We can already see a growing segment of businesses across the globe such as Codeway, BoxyCharm, Rocket Studio, Candivore and PIXIO, specialising in creating models to better understand their best customers and experimenting with strategies to acquire more of them.

In this paper, we make the case for why predicting lifetime value (pLTV) is necessary and detail the steps needed to begin your pLTV journey on Meta technologies. The final part of the paper becomes more technical as we introduce methodologies and cover the key decisions your teams will inevitably encounter. For example, should we develop user- versus cohort-based models? How should we define a lifetime? When should a prediction occur? And much more...

If you care most about business health for the long-term and you are keen to measure, predict and execute strategies based on the future value of new customers, then this paper is a great first step.

Kai Herzberger,
DACH Group Director, Meta,
Berlin, Germany.

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1.0

Introduction

1.1 Why would a business need to predict its customers' value?

Why would a business want to concentrate on the lifetime value (LTV) of its customers, adopt a new KPI or alter internal reporting lines? The short answer is profitability. In this introduction, we want to give the reader a better understanding of why LTV, in particular the ability to predict LTV or pLTV (hereafter LTV and pLTV are used interchangeably unless otherwise stated), should be regarded as the most important metric for business success.[1][2][3]

Businesses often focus on profitability rather than revenue growth during economic uncertainty and limited financial resources.[4][5] Yet, while the ambition to grow profitably is increasingly a common theme of recent earning calls, it is not always followed up with specific strategies to achieve it.[6] An LTV-focused approach to customer acquisition offers a significant advantage over short-term return on ad spend (ROAS) and cost tactics in terms of building a profitable business. **If a business can identify the most profitable customers early in the relationship, it can maximise the gains from the most loyal customers while minimising the losses from trying to persuade customers who have a low chance of becoming profitable in the long run.** [7]

The ability to identify profitable customers is accelerating due to the application of machine learning models to customer value. These technological advances are equipping more marketers with the unprecedented ability to predict the future unseen value of new customers and at a faster and more efficient rate than ever before. In turn, it can help address one of digital advertising's fundamental flaws: optimizing for short-term conversions rather than long-term revenue.

SOURCES: [1] Markey, R. (2021, June 2). Are you undervaluing your customers? Harvard Business Review. Retrieved August 25, 2022, from https://hbr.org/2020/01/are-you-undervaluing-your-customers, [2] Purcell, B. (2021, August 2). Make customer lifetime value your Polaris for long-term growth. Forrester. Retrieved August 25, 2022, from https://www.forrester.com/report/Make-Customer-Lifetime-Value-Your-Polaris-For-LongTerm-Growth/RES150315, [3] Taneja, V., & Roberge, M. (2021, May 5). The One ratio every subscription business needs to know. BCG Global. Retrieved August 25, 2022, from https://www.bcg.com/publications/2017/corporate-development-one-ratio-subscription-business-needs-to-know, [4] Markey, R. (2021, June 2). Are you undervaluing your customers? Harvard Business Review. Retrieved August 25, 2022, from https://hbr.org/2020/01/are-you-undervaluing-your-customers, [5] McIntrye, E. (2022). The State of Marketing Budget and Strategy 2022. The annual CMO Spend Survey Research . Retrieved August 25, 2022, from https://www.gartner.co.uk/en/marketing/research/annual-cmo-spend-survey-research, [6] Abdolvand, Neda & Albadvi, Amir. (2014). Customer Lifetime Value: Literature Scoping Map, and an Agenda for Future Research. [7] Abdolvand, Neda & Albadvi, Amir. (2014). Customer Lifetime Value: Literature Scoping Map, and an Agenda for Future Research.

“The purpose of business is to create and keep a customer”

Theodore Levitt [8]

“LTV is something we’ve kept track of for a very long time. Without tracking LTV we were undervaluing what the customers were bringing to us. It also allowed us to have a unified view on the business; we went from asking ‘what’s the optimal CPI for Paris, or New York?’ to really understanding what the actual long-term value is, and making much better decisions.”

Liam Branaghan - Performance Marketing Lead, Uber Eats, EMEA

1.2 What do we mean when we say ‘lifetime value’ and ‘predicted lifetime value’?

LTV represents the average revenue generated by a customer over the course of their relationship with a company. A customer’s historical value or lifetime value to date is easy enough to grasp. Calculating LTV begins with summing the value a given customer has already generated for a business. These calculations can become challenging if businesses don’t have their own unified data — a point developed in section 1.5.

SOURCES: [8] Although the full quote is usually attributed to Peter Drucker, I believe his first published quote was ‘the purpose of a business: to create a customer’ in ‘The Practice Of Management’, this was then expanded on by Levitt in ‘The Marketing Imagination’ to include the repeat business element in ‘...and keep a customer’

However, relying on historical value is not always a good metric to inform future marketing strategies. To begin with, a business would have to wait a significant amount of time before being able to assess the value of customer acquisition campaigns. But the more substantial point is that customers who have already been acquired have variable likelihoods of staying with a business into the future. Some customers might have a low historical value as they've only recently started purchasing. Nonetheless, if those customers come back regularly looking for their favourite goods then there's a high chance their future value will be significant. Other customers may have a high historical value, but they might no longer be willing to be with the business. Any dollar spent on them will be a dollar wasted. In other words, **a customer's historical value is not the same as their future estimated value.**

In contrast to historical value, predicted lifetime value (pLTV) can estimate future value. pLTV models leverage information within a short timeline (sometimes as short as two hours since initial user engagement) to create an accurate prediction of the future value. For example, a prediction for a given customer's day 30 LTV could be made within two days of the app install or registration date. Such models provide a glimpse through the foggy window of uncertainty into the future value a customer will generate for the business.

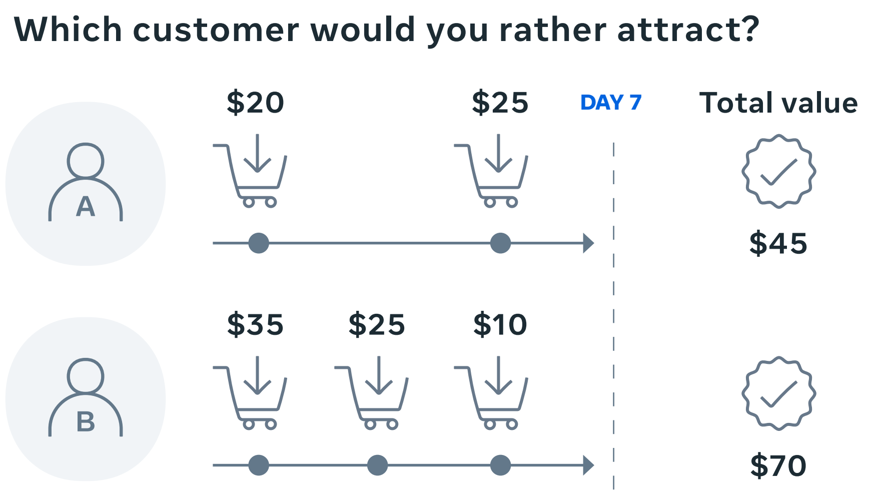


Figure 1: Comparing new customers based on short-term sales value.
For illustrative purposes only.

To demonstrate this point, we can consider an ecommerce example, although the underlying concept applies generally whether we think of an app service or a retailer.

Here is an example of two new customers that a business has just acquired (see figure 1). If it's only been a couple of hours or days after their initial purchase, it's easy to see the difference between them.

At this point in time, the first customer spent 45 dollars over two products, while the second customer spent 70 dollars over three products. It seems clear that if we had to prioritise which customer to invest our efforts and marketing budgets in, it would be the second. However, this is only true because we're looking at the current historical value rather than the predicted one.

As time passed, the second customer stopped purchasing from us. Perhaps they were responding to a short-term promotion or were only looking for specific goods (see figure 2). Whatever the reason, the first customer has increased in value over time and now represents a total value of 120 dollars. She is more loyal to the brand and regularly purchases her favourite products.

Which customer would you rather attract?

Figure 2: Comparing new customers based on longer-term sales value. For illustrative purposes only.

The situation is different than we initially thought. The short-term revenue turned out to be a weak indicator of the lifetime value. To return to the original question: Why would a business require a predicted lifetime value model? The answer is to be able to predict situations such as these.

If a business could estimate the probable future value of a customer, it could prioritise marketing investment accordingly. A pLTV model can take important predictive signals such as customer purchase history, demographics, quality indicators of customer service and customer engagement and much more to help find the customers most valuable over time. [9]

SOURCES: [9] Wang, X., Liu, T., & Miao, J. (2019). A Deep Probabilistic Model for Customer Lifetime Value Prediction. arXiv: Applications

In the context of gaming, user engagement behaviours like time spent in the game, levels achieved or sending invitations to friends can be highly relevant indicators of lifetime value of a user rather than what can be understood from purchase data itself. For ecommerce businesses, besides demographic characteristics, behavioural prediction signals could be the type of products browsed or purchased, search keywords, email subscriptions, registrations, time spent on site and so on.

On the other hand, acting on immediate short-term revenue or today's or yesterday's results may lead to missed opportunities and overspending on customers who represent low value to the business over time as could be seen in the example above.

Practitioner evidence supports the assertion that businesses who invest in, and activate, customer insights drive better performance. According to a 2017 Bain & Company survey of roughly 500 companies, market leaders exhibit a set of characteristics that set them apart from the bottom 25% of companies. [10]

What exactly do these market leaders do differently?

Market leaders are:

3.5x

More likely to embed employees in marketing who specifically focus on understanding the customer's end-to-end experience.

1.9x

More likely to align their strategy with customer needs rather than channel needs.

1.9x

More likely to scrutinise customer lifetime value in addition to more traditional last-touch metrics such as ROI, customer acquisition cost and clickthrough rate.

1.5 – 2.9x

Higher revenue uplift for Market Leaders by building and using insights from CRM to build customer value and enable marketing activations.

In short, **when a business focuses on understanding and increasing the customer value, its profitability increases.**

SOURCES [10] Beaudin, L., Dennehy, B., & Grudnowski, J. (2017, April 29). Customer lifetime value: A better compass to guide your marketing automation. Bain. Retrieved August 25, 2022, from https://www.bain.com/insights/customer-lifetime-value/

1.3 Is LTV merely a marketing strategy?

While we focus on the benefits of using the LTV or pLTV strategies in marketing, it is often used as a more comprehensive strategic approach to business profitability involving multiple business functions (see figure 3).

Figure 3: How LTV influences the strategy of critical business functions

LTV has been helping businesses make strategic business decisions since the 1970s by helping them understand how much they can afford to spend on a consumer to keep a positive return on investment.[11] For senior management, this insight into customer value and expected revenue and costs means understanding business performance in terms of long-term value. It helps to focus investment efforts across the organisation (product, finance, customer services, sales and marketing) and helps guide performance management conversations. LTV insights can inform product roadmaps and user journeys by providing answers to fundamental business questions such as ‘What product should we build that customers will engage more with and pay for?’ Similarly, finance teams would also pay close attention to questions such as ‘Which product or customer segment are profitable and which are not?’ and customer service would want to understand how their efforts impact the retention and loyalty of customers. As can be seen in the figure above, LTV influences the strategies of other critical business functions outside of marketing, which is just one response to the business challenge of finding ways to drive profit.

SOURCES [11] Burelli, Paolo. (2019). Predicting Customer Lifetime Value in Free-to-Play Games. 10.1201/9780429286490-5.

1.4 Are pLTV strategies only relevant for certain businesses?

There are industries that are highly sensitive to a longer-term evaluation of customer value: businesses where growth by itself is insufficient and success depends on tracking the longer-term business impact of decisions. [12]

Consider business models where payback is not immediate but delayed to a future time after the acquisition, install or free trial period. Subscription, financial services, education and gaming are all such industries with a long payback window. To break even might take more than 6 to 18 months from when a user signs up or a customer submits an application.

Businesses such as these depend on increasing customer retention and decreasing churn. In gaming, paying users account for only a small portion (about 3.8%) of the customer base but generate the majority of revenue.[13] As a result, identifying and acquiring higher value customers becomes a top priority. This is not to say that pLTV strategies are focused on targeting only the highest value customers. Rather, pLTV ensures all acquisitions are profitable regardless of the individual value of a user.

In other words, there may be a large and profitable audience above the cost of acquiring customers but below the top 1% of payers.

Long-term value is also widely applicable to other industries like ecommerce and retail advertisers as our previous illustrations showed. The most common commerce advertisers have relatively short purchase cycles and high transaction volume. However, profitability is heavily impacted by repeat purchases and product returns.

In summary, pLTV is particularly relevant for business models that are more dependent on either delayed customer payback or retention for their economic success than others — for example, subscription services and gaming. But that doesn't mean an pLTV focus is not relevant for a wide range of businesses such as those in commerce where future payback may be uncertain and returns can eat into profitability.

The following sections cover a range of options for advertisers to translate their interest in pLTV into action on Meta technologies.

SOURCES [12] Taneja, V., & Roberge, M. (2021, May 5). The one ratio every subscription business needs to know. BCG Global. Retrieved August 25, 2022, from https://www.bcg.com/publications/2017/corporate-development-one-ratio-subscription-business-needs-to-know [13] AppsFlyer. (2022, July 16). Lifetime value: The cornerstone of App Marketing. AppsFlyer. Retrieved October 13, 2022, from https://www.appsflyer.com/resources/reports/ltv-app-marketing-cornerstone/

1.5 Building the four enablers of a pLTV strategy

There are four foundational components to setting up a successful pLTV strategy

The Enablers of LTV

Customer centricity:

Does the business look to drive value from a customer perspective instead of just the number of transactions? Does it have a unique customer identifier to connect transaction data across systems?

Data and technology:

What infrastructure is needed to store, transform and model user data? To what granularity is this data available, and how well is the business equipped to pass this data back to publishers like Meta in a privacy safe way? For example, advertisers can use the Conversions API to share user consented data in a safe and secure way with Meta.

Analytical resources:

What kind of analytical resources are available (both in-house and external) to create and maintain predictive models — for example, statisticians, data scientists, data engineers or third-party solution providers? There are a wide range of LTV models of increasing complexity in the industry. But the best model is one that solves your specific business challenge.

Breaking internal silos:

Do finance and marketing share the same goals? Do they share a holistic business perspective, one that facilitates internal conversations, promotes alignment and understanding across the various functions on customer value? (For example, business, marketing and finance should speak the same language and look at the same KPIs.)

Figure 4:The four enablers of a pLTV strategy

In practice, each of these enablers is intertwined, and if marketers care about value enough to develop a pLTV model, then many, if not all, of these enablers will be necessary. For instance, consider the need for a customer identifier to connect transaction data from different touchpoints (web, app, in-store). A company would need to be both customer-centric and have the right data infrastructure in place to answer this question.

And if a business cares about value but does not yet have a pLTV model, then they'll need to advocate for support from senior leadership to build the other enablers. The doors to this strategic shift need to be opened simultaneously by the executives, the business intelligence teams and the teams responsible for marketing management.

"Our journey started within the marketing department but would not have been successful without the C-level support. When we were able to showcase the value of the solution to the entirety of the business, we received the support we needed to scale it across the business units, reaching outside of marketing. It's also important to realize that it is a journey, you can start quite simply by tracking the pLTV metrics in parallel with the ones you've always been using. And then slowly and steadily build from that, eventually embracing the pLTV metric as your main KPI."

Liam Branaghan – Performance Marketing Lead, Uber Eats, EMEA

2.0

How can advertisers activate their LTV/pLTV strategy with Meta?

Marketers have multiple options no matter how far along their business is on an LTV/pLTV journey. These options span measurement, targeting and bidding, and advanced optimization use cases (see table 1).

The measurement, targeting and bidding use cases can be used with models of any complexity. Marketers who are in the early stages of developing their first model can use it to enrich reporting, decide winners between strategies and improve targeting. While other marketers who are trying to improve their model, pushing it to achieve its full potential, can also avail of advanced optimization.

Table 1: Vertical-specific LTV strategies on Meta technologies

Business type	LTV/pLTV* strategy on Meta technologies		
	Measurement	Targeting & Bidding	Optimization
APP Gaming Tech Services **SUBSCRIPTION** Entertainment Education **COMMERCE** eCommerce Retail	**IN-CHANNEL:** • Enrich measurement metrics in Meta Ads Manager reporting (for example, long-term ROAS, LTV to CAC ratio) • Leverage LTV/pLTV as success metric for Conversion Lift, A/B Test and GeoLift **CROSS-CHANNEL:** • Incorporate LTV/pLTV in MMM**	• LTV/pLTV-based lookalike audiences • Tailored bidding strategy based on LTV/pLTV customer segmentation • Exclude low LTV/pLTV lookalike audience with broad targeting strategy	• Custom event optimization (CEO) • Value optimization (VO) • Post-conversion optimization (PCO)

Next, we'll review a sample of those strategies and present examples of advertisers who have successfully applied them.

* Both LTV and pLTV models support measurement, targeting and bidding strategies. Only pLTV meets requirements for campaign optimization.

** MMM: Marketing Mix Modeling

2.1 Measurement

2.1.1 Enrich Reporting.

The foundational use case relevant for all verticals and businesses is to enrich reporting metrics in Ads Manager with KPIs that reflect long-term value (for example, pLTV ROAS, LTV to CAC ratio).

How to set up pLTV in Ads Manager reporting

Businesses with a pLTV model in place can pass pLTV signals to Meta via their Conversions API, SDK or MMP integration as a custom web or app event. Once the pLTV custom event is in place, web advertisers can create a custom conversion to enable reporting in Ads Manager. App advertisers need to create a custom event optimization campaign that optimizes towards this custom event to enable reporting. This is because app custom event reporting is only supported when there's at least one campaign optimizing towards that custom event.

Watch out for attribution

Marketers using pLTV in Ads Manager must understand the limitations of attribution. All reporting within Ads Manager is subject to attribution logic and will offer a filtered view of performance. Therefore, marketers should use pLTV as a success metric in Conversion Lift when making strategic decisions.

2.1.2 Decide on winning strategies based on pLTV.

Instead of evaluating Meta ad campaigns based on immediate ROAS or cost per outcome, marketers can evaluate campaign success from a lifetime value perspective. To avoid the situation where short-term gain is translated into a long-term loss, we need to rely on pLTV as the success metric.

Once pLTV reporting is enabled in Meta Ads Manager, advertisers are able to create A/B or Conversion Lift to compare different tactics and strategies against each other — for example, video versus static, different ways of bidding, different optimization events, the audiences you target and so on. pLTV can also help determine better performing strategies from location-based experiments, such as GeoLift.

If the success metric is pLTV, you can have greater confidence that the strategy in the winning test group is going to bring higher long-term value. Remember that the results of A/B tests will be attributed results from Ads Manager, as they do not have a control group, and results will not be incremental as they would be with Conversion Lift or Geolift.

2.1.3 Using LTV/pLTV for cross-channel media measurement with MMM.

Marketing mix modeling (MMM) is a powerful and privacy-friendly tool for marketers to understand and optimize their advertising mix. An exciting area of new development is to use LTV/pLTV for cross-channel media measurement with MMM. Instead of modeling advertising's direct, short-term effects, advertisers who have an LTV model also have the option to evaluate which channels or channel mix are contributing to higher LTV.

MMM is a very flexible measurement technique that can be used to model any business outcome or dependent variable (sales, revenue, market share, NPS scores, loyalty scores.

Therefore, using pLTV as dependent variable in MMM is possible since it varies over time and is impacted by marketing mix inputs (media spend/paid impressions across channels, sales channels, seasonality etc).

For instance, rather than using MMM to model daily or weekly sales, which reflects short-term performance, it can leverage pLTV from users acquired on a daily or weekly basis as the dependent variable in the model. Using pLTV as the dependent variable would allow us to evaluate the ways in which spending variations across media influence the type of users being acquired by that media mix, which will influence how they engage with the business in the long run. Using LTV/pLTV for cross-channel media measurement with MMM is an exciting area of exploration and innovation.

2.2 Targeting and bidding

Target high-value audiences.

The pLTV insights can also be used to create value-based lookalike audiences. If a business is able to pass to Meta not only the users' identifiers but also the predicted LTV values, by using the value-based lookalikes, Meta ads campaigns can target ads to people who look like your highest value customers.

Tailored bidding strategies based on pLTV.

For businesses where LTV can vary drastically (such as gaming advertisers), they could consider applying tailored bidding strategies based on LTV segmentations, where higher bids will be placed for segments with higher LTV. Tailored creatives can also be applied based on the preferences of users from different LTV segmentations.

Exclude low-value lookalike audiences with broad targeting strategies.

Businesses using broad targeting strategies (commonly seen among commerce advertisers that operate in many markets) can also optimize towards higher value consumers by excluding low-value lookalike audiences without complicating the ad account structure.

2.3 Optimization

Acquire high-value new customers with custom event optimization.

If the business is able to predict whether a newly acquired customer is going to be valuable in the future, it can pass high-pLTV acquisitions to a custom event and train the Meta ad delivery system to find more high-pLTV acquisitions.

Post-conversion optimization.

A similar result might also be achieved by using post-conversion optimization, where a business can indicate if a customer acquisition is specifically valuable up to 28 days after it happened. So subscription businesses are now able to send first payment signals to allow deep-funnel optimization. Car dealerships can optimize for people who end up purchasing a car after a test drive. And fashion retailers can optimize towards customers who keep a certain basket value (customers who do not return the whole order or a certain percentage of their order).

Maximise long-term ROAS with value optimization.

Businesses across all verticals can also leverage value optimization campaigns, where a machine learning algorithm can first tell the difference between high-value customers and low-value ones and then prioritise bidding for the highest value customers. By automatically bidding more for people who are likely to generate higher LTV, businesses can rest assured that campaigns are achieving maximum long-term ROAS.

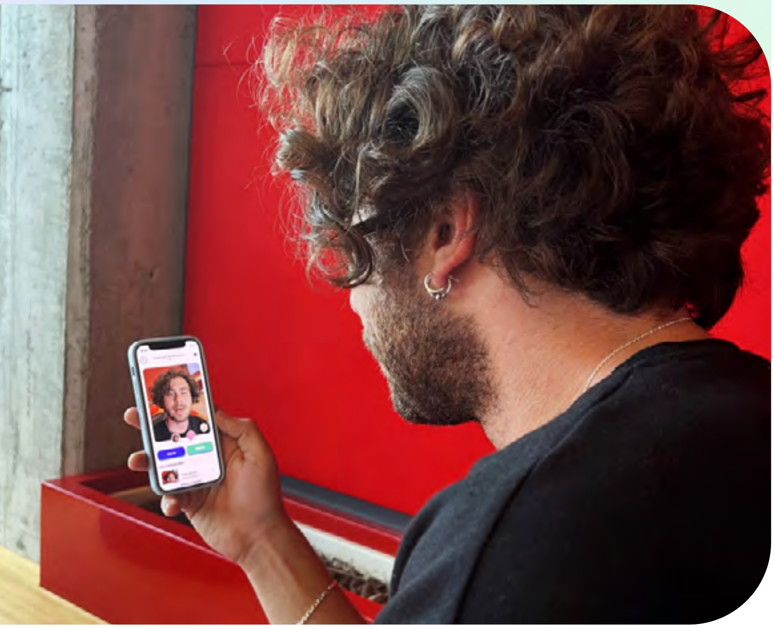
2.4

pLTV success stories on Meta

CASE STUDY

Codeway

The Turkish software company **increased subscriptions by 32%** after using custom event optimization on Meta technologies to help identify potential customers with the highest lifetime value.

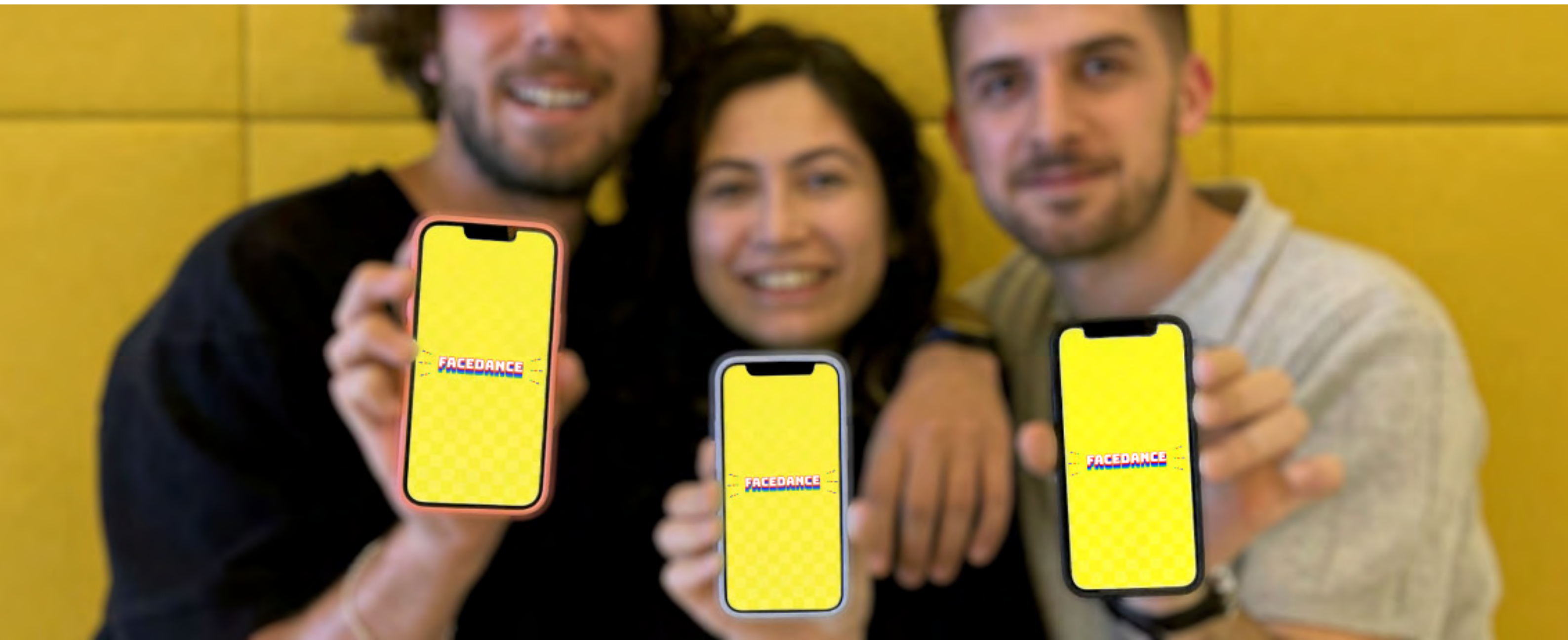


The Story

Codeway was founded in Istanbul, Turkey, in 2020 with the goal of turning strong ideas into vertical-leading mobile applications. Today, Codeway's flagship product, Cleanup, is among the most downloaded utility applications in the US. The company wanted to attract new subscribers who were likely to become long-term customers for its mobile software-as–a-service. To predict the long-term value of new customers, it worked with Churney, a solutions provider that specialises in detailed predicted lifetime value models.

The Goal

To achieve its goal, Codeway created a custom event to indicate the acquisition of a highly profitable customer based on a predicted lifetime value model. This new strategy was tested against Codeway's previous customer acquisition campaigns using a Meta conversion lift test. This enabled Codeway to measure the success of the strategy based on incrementality and LTV rather than short-term metrics.



CASE STUDY

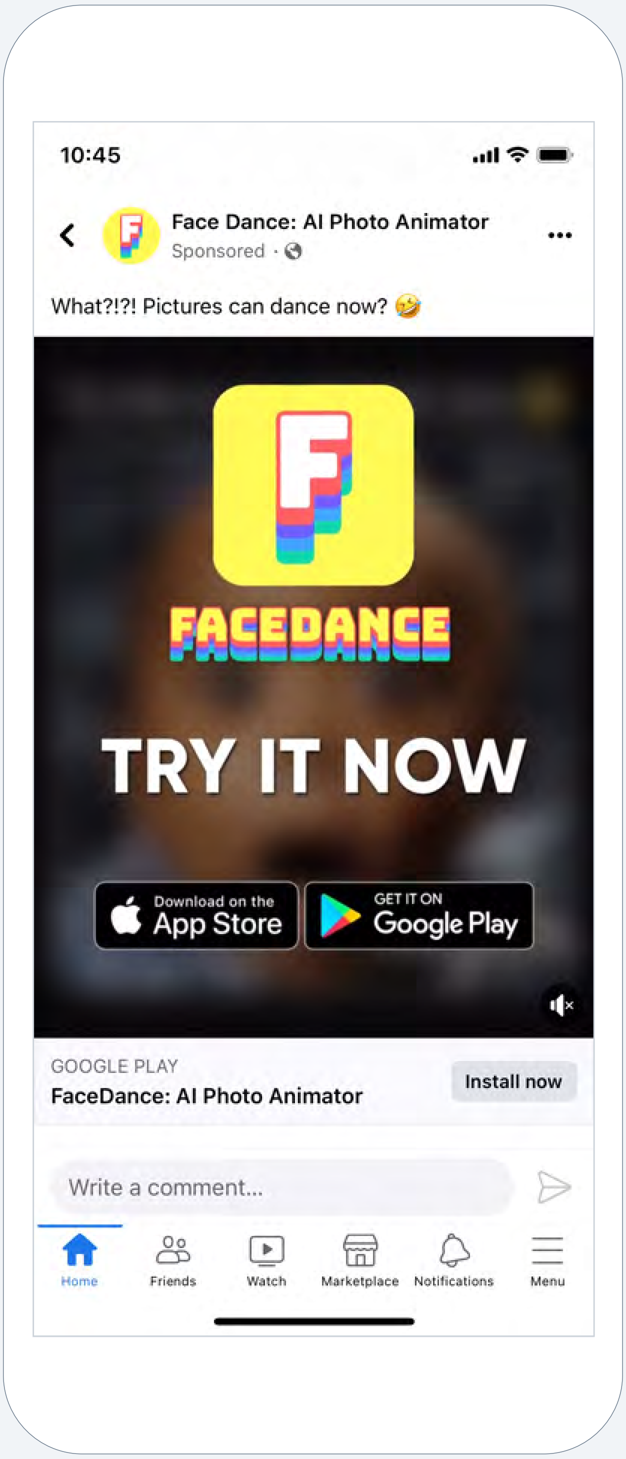
The Results

Between August 2022 – September, 2022, the Custom event campaign achieved:

- **32%** more incremental subscriptions versus business as usual
- **19%** reduction in the cost per incremental high-value customer acquisition versus business as usual
- **20%** higher predicted lifetime value of newly acquired customers versus business as usual

"By optimizing our campaign for the predicted lifetime value event, we were able to attract higher-value users, provide better signals to Meta's algorithm, and increase our return on ad spend. We will pursue this strategy for future campaigns."

Cantug Sugun
Marketing Team Lead, Codeway



CASE STUDY

BoxyCharm

The American beauty subscription box **increased its four-month retention rate by 23%** after implementing the Conversions API with pLTV to appeal to new subscribers who were most likely to become loyal customers, and predicted even higher increases after 12 months.

The Story

BoxyCharm is a monthly beauty subscription box, with more than one million subscribers in North America. BoxyCharm offers each subscriber four or five full-size beauty products or items each month, from both independent and established brands.

The Goal

Because BoxyCharm is a subscription business, its success depends on retaining existing subscribers while attracting new people to its service. It therefore wanted to optimize its ads to appeal to people who were likely to have higher lifetime customer value, rather than just focus on reducing its subscriber acquisition costs.

The Solution

Knowing that the top 30% of lifetime value customers are responsible for 70% of its revenue, BoxyCharm worked with predictive user acquisition platform Voyantis to optimize its ad campaigns for high lifetime value from the Conversions API. It then shifted its ad investment to concentrate on reaching people who were most likely to remain loyal customers.

CASE STUDY

The Results

With the help of the Conversions API, BoxyCharm has been better able to find and attract loyal customers on Meta technologies. From July 17–31, 2021, the campaign achieved:

- 23% higher retention rate at the end of a four-month period
- 35% predicted higher retention at the end of a six-month period
- 81% predicted higher retention at the end of a 12-month period
- 30% higher return on ad spend at the end of a 12-month period

"After we understood we have a significant lifetime value variance within our subscriber base, we worked with our Meta and Voyantis teams to create a prediction model that uses the Conversions API to enable us to optimize our acquisition investment on Meta technologies for lifetime value and not just first-time purchase value. Using this prediction model, we were able to improve the 12-month return on ad spend by 30%."

Alessandra Sales, VP of Growth, BoxyCharm

CASE STUDY

Rocket Studio

The Vietnamese gaming studio **increased revenue by 6 times** after implementing value optimization on Meta technologies that optimize towards acquiring high-value players, measured by an innovative geography-based framework that accurately measures the incremental impact of its iOS campaigns.

The Story

Rocket Studio is a Vietnamese gaming studio that primarily develops arcade action games, including the popular and highly-rated “Galaxy Attack: Space Shooter”. The company aspires to bring the best experience to players while bolstering the position of Vietnamese games on the global stage.

The Goal

Apple’s SKAN protocol made it challenging to identify potential high-value players and accurately measure iOS campaign effectiveness. Rocket Studio needs a new solution to better identify and acquire high-value players and accurately measure the effectiveness of its iOS campaigns.

The Solution

Rocket Studio collaborated closely with Facebook Gaming and Meta Business Partner, AppsFlyer, to design a holistic solution that improves ad delivery and enhance its measurement capabilities. The team first projected day-30 LTV using AppsFlyer’s Predict solution and leveraged Meta’s value optimization solution to acquire high-value players. Next, AppsFlyer and Facebook Gaming designed a geography-based framework to measure incremental revenue of the new strategy against its regular app install optimization.

CASE STUDY

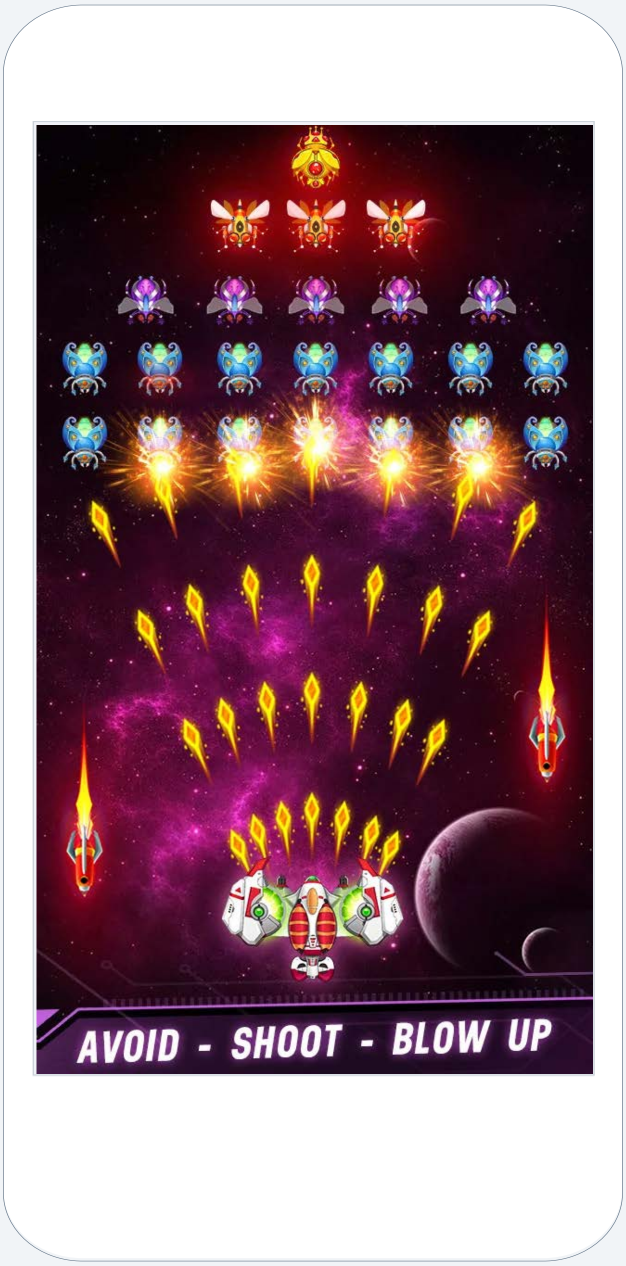
The Results

The new pLTV strategy proved to be highly effective in boosting long-term revenue: :

- 6 times higher revenue from pLTV value optimization compared to previous app install campaigns
- 42% higher day-7 return on ad spend compared to previous app install campaigns

"Meta has always been our trusted partner in acquiring high-value players. With the holistic support of Meta, we were able to continuously experiment and implement innovative approaches to increase our game performance. This test in particular, has helped us evaluate the exact effectiveness of value optimization and has given us more confidence to scale this strategy further to more games."

Hanae Vu
UA Marketing Leader, Rocket Studio



CASE STUDY

Candivore

The Israeli mobile gaming company **lowered the CPA of acquiring highly engaged users by 420%** by reaching gamers with a high long-term value rather than focusing on short-term gains. By acquiring these users at a lower cost, Candivore increased the overall lifetime value and profitability of its game. The company realised that 80% of such users were being overlooked with its previous advertising strategy.

SOURCES: [14] Gaming startup candivore raises $10 million to build on Match Masters Success. ctech. (2022, May 26). Retrieved October 5, 2022, from https://www.calcalistech.com/ctechnews/paper/

The Story

Candivore is a gaming startup and responsible for one of the most popular mobile games Match Masters which has more than 30 million downloads across Google Play and Apple Store.[14]

The Goal

Candivore identified an opportunity to target ads to 'late bloomers' (users who showed high LTV over a longer time period, beyond the seven-day conversion window. Therefore, its goal was to reach new audiences and scale further using predictive signals for higher LTV.

The Solution

With Meta's App Event Optimization, and with lifetime value solution provider Voyantis, the company built a prediction model to target highly engaged users. They optimized their user acquisition campaign to target similar users to those who proved to have a high lifetime value and purchased outside of the regular conversion windows. This led to the creation of a custom event to reach out to those valuable users.

CASE STUDY

The Results

- **420%** lower CPA of highly engaged users
- **12%** Return on Ad Spend uplift by day 180
- **220%** lower cost per impression

"We wanted to reach new audiences and scale further using predictive signals for higher LTV. Voyantis's prediction based UA solution combined with Meta's new App event optimization product for custom events drove lower CPIs, higher engaged users and higher mid to long-term ROAS. Overall we see great potential in this strategy to acquire valuable users efficiently and maximize LTV of our games."

Ilya Agron,
Chief Operating Officer, Candivore

CASE STUDY

Pixio

The Hong Kong-based mobile gaming studio **achieved 31% higher revenue per purchase** by connecting predicted lifetime value models with custom events within app event optimization for Meta ads.

The Story

PIXIO is a mobile gaming studio that specialises in casual and single-player mobile games. Since its inception, PIXIO has launched four hit titles that appeal to gamers worldwide, namely Tap Tap Trillionaire, Tap Tap Evil Mastermind, Game of Earth and Summoner's Greed.

The Goal

Three years after the launch of PIXIO's flagship title, Summoner's Greed, the mobile gaming company sought to expand its audience and reach new players with high long-term value.

The Solution

PIXIO decided to connect the predicted lifetime value (pLTV model with custom event optimization to assess the lifetime value of new players by day 30. After building a highly accurate prediction model with Pecan, an accessible, low-code predictive analytics company, the team created an app event optimization campaign optimized towards custom events. This allowed PIXIO to optimize to potential players within the top 1% of pLTV values.

PIXIO also set up a two-cell lift test to measure the incremental value delivered from the new strategy. The first cell held a dedicated campaign focusing on the custom event created through the pLTV model. The second cell had the existing business-as-usual app event optimization campaign optimized for the purchase event.

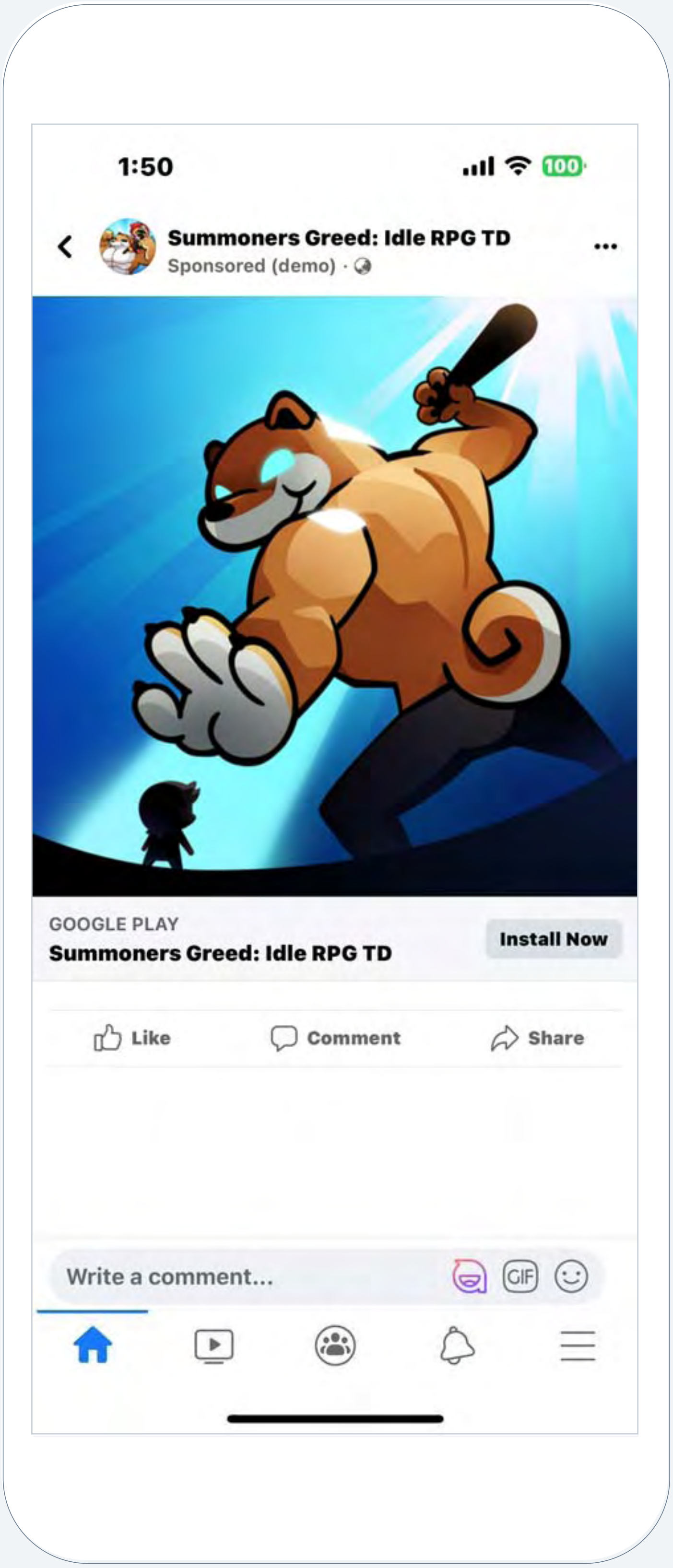
CASE STUDY

The Results

- **31%** higher revenue per purchase with app event optimization for predicted lifetime value custom events, compared to usual campaign
- **18%** higher incremental return on ad spend with app event optimization for predicted lifetime value custom events, compared to usual campaign
- **4%** lower cost per install with app event optimization for predicted lifetime value custom events, compared to usual campaign

"We are very happy to have the opportunity to test and also add pLTV testing to our campaigns. The pLTV modeling allowed us to explore and test campaigns with machine learning targeting options. Our next step is to reproduce and use this approach on a larger scale, hopefully across all our campaigns."

Ricky Leung
CEO, Pixio Ltd.



3.0

A brief introduction to LTV and pLTV methodologies

When decision makers embark on an LTV or pLTV project, they will soon find that there is no consistent terminology, nor is there a single agreed upon practice for calculation and prediction.[15] Instead, modeling LTV consists of a vast collection of techniques.[16] The majority of methods rely on purchase data. However, with the increasing quantity, variety and quality of customer data, pLTV calculations have expanded to include other types of customer engagement data with the business. While on the modeling side, the norm is for a wide range of ever evolving modeling methods and calculations depending on what you're trying to figure out and what assumptions you're willing to make. Given this complexity, how should someone decide which method is right for their business?

SOURCES [15] Burelli, Paolo. (2019). Predicting Customer Lifetime Value in Free-to-Play Games. 10.1201/9780429286490-5. [16] Fader, P. S., & Hardie, B. G. S. (2009). Probability Models for Customer-Base Analysis. Journal of Interactive Marketing, 23(1), 61–69. https://doi.org/10.1016/j.intmar.2008.11.003

3.1 How do I decide which method is right for my business?

What constitutes the right method for a business is determined by how the model is going to be used in light of the available resources. For example, will the calculation be used for financial reporting, customer segmentation or marketing optimization? Will you focus on existing or new customers? For each, model granularity will become an important factor to consider. Hence, we categorised LTV methods by the granularity of calculations. (See table 2 below. For a summary of the similarities and differences of model types, see appendix a.)

Table 2: How LTV granularity maps to business use cases

LTV granularity	What does it provide?	Use cases
1. Total customer base LTV	This gives the average LTV value for all users.	Senior management often use metrics like LTV to CAC ratio to reveal the true health of the business and make strategic decisions.
2. Cohort-level	This gives the same LTV value for a cohort of users.	Finance or marketing departments often use cohort-level LTV metrics to surface both highly profitable business or customer segments and non-profitable ones, which is crucial for unlocking the next level of profitable growth.
3. User-level	This gives individual-level LTV value for each user.	User-level LTV is primarily used by marketing departments for two example use cases: • Customer segmentation to enable tailored customer life cycle activations • Marketing optimization (pLTV models) for optimizing towards high-value customers in near real-time

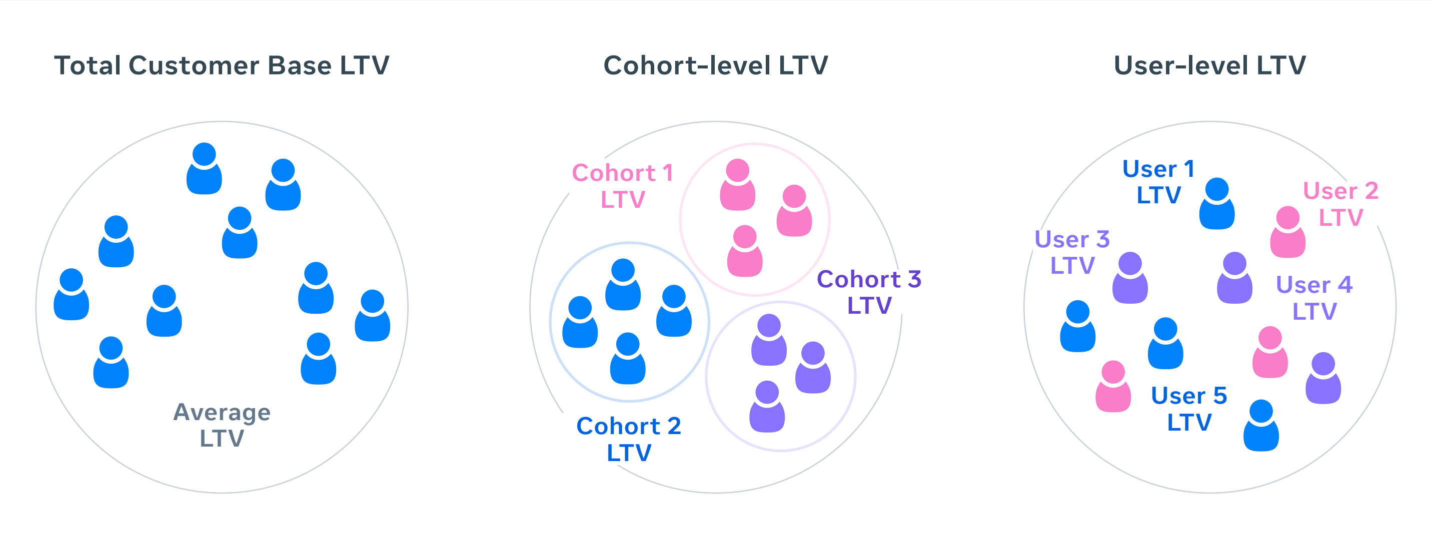


Figure 5: Granularity of LTV prediction

3.1.1 Total customer base LTV

The simplest way to calculate high-level LTV for a business is by the formula LTV = Average Order Value x Number of Orders x Retention Period. This formula assumes uniform customer behaviour and adopts a constant average revenue per customer and cost. Yet, this simple calculation is a profound first step towards a customer-centric transformation. It turns on the 'value' lens for senior management when evaluating the true health of the whole business, and it provides guidance on whether the business should focus on scaling growth or increasing profitability.

3.1.2 Cohort-level LTV

Cohort-level LTV goes one level more granular. Cohorts group together related users who share characteristics that distinguish them from other groups of users. Cohorts can be defined by one or multiple dimensions, depending on the use cases.

In cohort models, where data is not available for each customer, calculations are based on the average revenue or retention of groups of users. In the revenue model, the value of total transactions is forecasted based on a sample of daily users and their transactions. Whereas in the retention model this model assumes that average revenue per daily active user (ARPDAU) is constant.

> "The cohort level predictive model is being used by our finance team. It allows us to understand if we are profitable and decide on budgeting for the weeks and months to come. This is also how we steer our marketing decisions. Individual-level models are harder to interpret and have a higher variance. They're useful for performance marketing teams when we work on ranking systems, bidding strategies and optimization events for advertising."

Alexander Sterligov, Head of Marketing Technologies, Joom SIA

3.1.3 User-level LTV

User-level models can be grouped based on their prediction coverage for consumer types. Some user-level models predict only for existing customers who already have purchase history — for example, BTYD or RFM models, while there are other advanced machine learning-based models that can predict LTV of users irrespective of whether the customer has already made a purchase or not.

Recency, Frequency, Monetary value (RFM) models:

RFM models are a very powerful tool that have been around for decades to help businesses segment their customers and apply tailored marketing or communication strategies based on each customer segment's behavioural characteristics. An example is sending new customers a welcome gift or sending a special offer to a customer who hasn't purchased or engaged with the business in a while.

An RFM model requires three pieces of information about each customer's past purchasing history: 'recency' (when the last transaction occurred), 'frequency' (how many transactions they made in a specific period) and 'monetary value' (the total transaction value in a specific period). The model then groups customers based on all three metrics and can rank them from 'good' to the 'bad' based on LTV rank.

Probabilistic models:

Probabilistic models use probability distributions to model LTV. They can be grouped into a large family of models known as Buy-Til-You-Die (BTYD).[17] BTYD models rely on purchase transaction data only and need a lot of historical data. The BTYD model could be more suited for established commerce business for users with existing history of purchase but can struggle to predict LTV for new users without much purchase history.

Machine learning models:

Machine learning models refer to a group of computational methods that use experience and/or past information as input to make predictions about new or unseen data (for example, supervised learning models, gradient boosting (GB) methods, deep neural network (DNN) models, random forest (RF)).

These models can estimate the value of customers based on multiple factors such as purchase history, customer demographics, behaviour patterns and reactions on the marketing communication (See appendix b for further reading on machine learning applied to LTV.) Adding relevant features helps to predict LTV with higher accuracy.

The estimation process for machine learning models contains two stages: training and making predictions. The prediction stage is generally very quick for the above models, but the training stage can take a longer time for DNN, GBM and RF models (hours or days for DNN).

SOURCES [17] How LTV prediction can improve sales & marketing strategies. Width.ai. (n.d.). Retrieved October 11, 2022, from https://www.width.ai/post/ltv-prediction-machine-learning

3.2 The challenges in designing predicted LTV models

There are several fundamental questions that arise when designing pLTV models:

i) What do we mean by customer lifetime?
ii) When does the prediction happen?
iii) How accurate is the model?

3.2.1 What do we mean by customer lifetime?

An early challenge is determining how long the prediction should be in order for it to be referred to as the customer's 'lifetime value.' The term 'customer lifetime' can have multiple meanings and be relative to the business model, or it can be an absolute length, such as at least six months or 12 months. Predictions can range from 7 day, 14 day, 30 day, 180 day to 12 months or 24 months. Whatever the appropriate period, it would likely be determined by business situations and user behaviours with the business.

A young growing company may want to recover the cost of marketing by focusing on users who can return the value within six months and thus may choose to focus on 180 day LTV versus other established businesses that understand that their users stay for two or three years. Based on user engagement behaviours, gaming advertisers frequently use shorter predictive models (7 days or 30 days) while ecommerce, retail or subscription advertisers tend to use longer predictive models (12 months or longer).

3.2.2 When does the prediction happen?

A second challenge is determining whether prediction occurs before or after the first purchase, which depends on when user identification happens.

A business will need to create a 'good enough' prediction fast enough in order to be able to optimize the campaigns towards this signal. The reason for speed in making predictions is due to different optimization windows on Meta technologies (1 day and 7 days). If a business can only estimate the pLTV 30 days after a customer is acquired, it might be useful for internal knowledge and measurement but cannot be used for campaign optimization (see section 2.0). Therefore, it is critical to generate a predicted LTV signal and pass it on for optimization within the 7 day optimization window. Thanks to machine learning methods, the advertisers in our success cases have been able to predict quickly and were able to execute successfully on Meta technologies.

SOURCES [18] M. Mohri, A. Rostamizadeh, and A. Talwalkar. Adaptive Computation and Machine Learning MIT Press, Cambridge, MA, 2 edition, (2018)

3.2.3 How accurate is the model?

No matter how simple or complicated the model, assessing model performance and accuracy is a key part of the process. Users of the model such as marketing teams who need to know how confidently they can trust the new pLTV signal when making decisions. Whereas the data scientists building the model need to know if the model can perform better.

Before deploying the model in production.

Marketers can use cross-validation methods (such as K-fold cross-validation) to account for model overfitting or selection bias. Cross-validation involves randomly partitioning data into training samples to train the model(s), validation samples used to validate the model(s) and test samples to see if model performance can be replicated. An effective model is one that can perform accurately on unseen data and so performance will be evaluated on how well the model can generalise to the test sample.

Typical model accuracy metrics include evaluating how much variance is explained by the model, for example R-squared and adjusted R-squared, as well as evaluating how much error is in the model, for example Mean Absolute Error and the Root Mean Square Error. In general, the key heuristic to keep in mind is that if a model can generalise with high accuracy, it means it will perform better at evaluating each new customer or user.[19]

There is an exception whereby marketers do not always need to accurately predict actual value. The main purpose of an LTV prediction model is to correctly separate high and low payers. One method of differentiation is to pay special consideration to the direction or rank of predicted LTV. For example, imagine we have three customers with an LTV of $2, $3, $100. Model one predicts the following LTV for those customers: $1, $2, $3, while model two predicts: $2, $2, $2. Model one is better for LTV prediction than model two because it can tell us that customer three will pay more than others. The two models can have the same error but model one is better for LTV prediction as it can tell us a customer will pay more.

SOURCES: [19] M. Mohri, A. Rostamizadeh, and A. Talwalkar. Adaptive Computation and Machine Learning MIT Press, Cambridge, MA, 2 edition, (2018)

After deploying the model in production.

All models degrade over time and need to be retrained and rebuilt. A model is trained on data at a particular point in time and model accuracy can deteriorate when any of the assumptions underlying the model change, for example due to large macroeconomic trends that affect customer behaviour like COVID or changes in business services.[20] Therefore, model reliability must be frequently monitored and measured. The actual update cadence can vary widely from every few days, quarterly to six months.[21]

There are several ways to account for distribution shifts (for example, differences between historical data sets used for training and real-time data that the model is applied to). One way to catch distribution shifts is by validating the predictions with actual 7 day or 30 day revenue to check if predictions fall into the right buckets (high, medium, low segments). This is an important validation exercise that can serve as an early warning sign.

3.3 From model accuracy to strategy success

While an accurate and generalisable model is the goal of performance assessment, it is important to note that good prediction does not imply causality. Models can predict outcomes but cannot tell you about the road not taken or what would have happened in the absence of this or that advertising strategy based on model predictions. Avoid misinterpretations by verifying the causal impact of advertising strategy via a randomised control trial test such as Conversion Lift or Geolift.

SOURCES: [20] Diliberto, L. (2021, May 21). When should you retrain machine learning models? phData. Retrieved February 28, 2023, from https://www.phdata.io/blog/when-to-retrain-machine-learning-models/ [21] Vanderveld, A., Pandey, A., Han, A., & Parekh, R. (2016). An engagement-based customer lifetime value system for E-commerce. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. https://doi.org/10.1145/2939672.2939693

3.4 Key pLTV model questions

Below is a summary of the most important questions to ask when building and deploying your pLTV model:

- **How is customer lifetime value defined?**
    - **How is the 'customer' defined?** (For example, cohort-level or user-level? New or existing customers?)
    - **How is 'lifetime' defined?** (For example, 14 days or 12 months?)
    - **How is 'value' defined?** (For example, pure revenue or profit?)
- **When are the predictions made?** (For example, before or after the first purchase?)
- **How soon are the predictions made?** (For example, within 2 hours or within 2 days of app install, registration or first purchase?)
- **Is the model cross-validated?**

3.5 Is your business ready to develop pLTV?

Meta does not build pLTV models for advertisers. However, marketers who believe LTV is too technical to develop in-house today can take advantage of the growing ecosystem of third-party LTV modeling solution providers such as AppsFlyer, Churney, Pecan, Retina, Voyantis and Explorium. All of these providers offer user-level predicted LTV modeling solutions. These are perfect for marketers seeking to transition from cohort-level models to user-level models.

4.0

Conclusion

4.0 Conclusion

LTV is often regarded as the most important metric for business success. Particularly in industries where profitability is impacted by delayed customer payback, customer retention, repeat purchases and product returns. One of the most exciting contributions to driving profitability is the recent application of machine learning to predict customer value. The ability to predict the future unseen value of new customers suggests new avenues for driving profitability and offers a compelling reason for why business leaders should adopt pLTV:

- Predicting and acting on the lifetime value of customers provides businesses with actionable intelligence and a set of strategies to drive profitable growth while minimising the impact of the increasing costs of user acquisition.
- Predicted LTV plays a key role in the signal-less world where it enables advertisers to leverage insights from their own first party data (CRM data) based customer insights to leverage ad solutions on Meta technologies.

For businesses already convinced of pLTV's potential but more interested in learning how to activate their models, we've presented strategies for how to leverage pLTV signals on Meta technologies. They are from the same playbook that advertisers such as Codeway, BoxyCharm, Candivore and PIXIO used to activate their pLTV models with great success.

We've also provided a brief overview of LTV and pLTV methodologies and their considerations. It's easy to get lost in the bewildering variety of definitions, calculations and methodologies. For businesses at the beginning of their journey, we recommend starting with the four enablers of a pLTV strategy and using them as a checklist to evaluate progress. If setting up a pLTV strategy still seems too technical, there is a growing ecosystem of third-party LTV modeling solution providers who provide user-level predicted LTV modeling as well as consultations to help businesses build in-house models.

In a nutshell, what actions can aspiring market leaders do to take advantage of pLTV?

- **Leverage the four enablers to start the value discussion.**
- **Choose KPIs that are closer to long-term business value. This can be done with models of almost any complexity.**
- **Don't let a lack of technical expertise slow you down — explore LTV solution providers.**
- **Test the efficacy of pLTV models on Meta technologies using one of the listed strategies.**

5.0

Appendix

5.1 Appendix A

Similarities and differences of model types

Table 3: How model type varies based on different assumptions of customer behaviour, prediction granularity and prediction availability

Model type	Uniform behaviour vs. variable customer behaviour?	Prediction granularity	Is prediction available for existing purchasers only?
Simple forecasting or linear multiplier	**Uniform customer behaviour** (for example, constant multiplier from day 1 revenue to LTV)	Aggregated or user level	Existing purchasers
Cohort-based LTV	**Uniform customer behaviour** (for example, constant retention curve or ARPU or other revenue multiplier)	Aggregated or cohort level	Cohort level, can be for payers or overall users
RFM models	**Uniform customer behaviour** (for example, constant RFMbuckets)	User-level	Existing purchasers only
Probabilistic models	**Variable customer behaviour** (varying RFM curves)	User-level	Existing purchasers only
Machine learning models	**Variable customer behaviour** (varying user behaviour engagement data)	User-level	All users (purchasers or non-purchasers)

5.2 Appendix B

Further reading

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5.3 About the Authors

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Paul leads strategy for independent agencies across Northern Europe where he consults on measurement methodologies — which ones to use, when to use them, how to use them, as well as how organisational operating models need to adapt to modern measurement needs. At The Centre for Innovative Human Systems, he co-authored research on community empowerment in Ethiopia. The research is shaping policy affecting over 1.8 million people in impoverished circumstances.

Qiong Wu,
Marketing Science Partner,
Meta, Stockholm

Qiong is the co-lead of the pLTV pilot, empowering advertisers to achieve profitable growth through pLTV strategies on Meta technologies and a trusted advisor to top global fashion retailers on omni-channel strategies. Throughout her more than 10 years at leading advertising agencies in the US, and at H&M and Meta in Sweden, Qiong's wealth of expertise has helped a diverse range of global brands accelerate growth by transforming their approach to measuring marketing effectiveness and implementing successful strategies..

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Mateusz is the co-lead of the pLTV pilot implementing pLTV solutions at Meta and a consultant to the biggest marketplaces in Europe. With an academic background in international affairs, Mateusz has pursued a career in media and experienced it both from agency's and advertiser's perspectives, having worked with Amazon, P&G, Toyota and Lexus, among others.

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Marketing Science Partner,
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Sharad has more than 10 years' of international experience leading high-performance teams in analytics and data science solutions for marketing, customer life cycle and consumer tech products.
He has consulted C-level executives from leading global digital businesses on data-driven strategies and initiatives to drive user growth and profits. At Meta, he currently leads customer analytics and measurement strategies for global digital businesses, apps and gaming companies to succeed in a rapidly changing privacy-first world.

Kai Herzberger
DACH Group Director
Meta, Berlin

Kai Herzberger is heading the commerce team at Meta for the DACH region. With his team he consults with clients on how to effectively do business and communication in an ever-changing marketing environment where business outcomes in a people-first approach are key.

5.4 Executive Sponsors

Sandra Hughes
Marketing Science Director
Meta, London

Sandra has more than 20 years' experience across clients, agency and digital media platforms. She has led teams of analysts, data strategists and within Meta, led Marketing Science teams across numerous markets and various vertical specialisms, all with the aim of helping clients grow their business through data driven strategies and supporting them in adapting to the ever changing media landscape.

Kate Minogue,
Marketing Science Senior Manager,
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Kate has over 10+ years experience in Analytics with roles ranging from Data Scientist to Leadership with specialism in marketing analysis and customer intelligence. Her focus is driving companies to make better decisions using data, statistics and machine learning and building the data and organizational strategies that underpin this.

Johan Kvist
Head of Marketing Science Nordics
Meta, Stockholm

Johan has more than 20 years' experience from leadership roles within analytics, data and consumer insights. He leads a team of Marketing Science Partners who work with advertisers across the Nordics. Many of these are headquartered in the Nordics with operations worldwide. Johan is passionate about helping all businesses grow by transforming marketing practices, grounded in data and science. He also has a passion for behavioural science.

Meta