ANALYSIS OF FACTORS INFLUENCING CUSTOMER LIFETIME VALUE IN THE HOME TEXTILES SEGMENT

by

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Head of the KSE Defense Committee, Professor [Type surname, name]

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CLV Customer Lifetime Value

WACC Weighted Average Cost of Capital

CAPM Capital Assets Pricing Model

ERP Equity Risk Premium

TBP Time Between Purchases

CHAPTER 1. INTRODUCTION

Customer Lifetime Value (CLV) is a key metric that allows companies to estimate the total revenue that a customer can bring over the entire period of cooperation. CLV is a company's net profit forecast associated with all future customer relationships (Fader et al., 2005). This research analyzes the factors influencing the CLV of customers of the Ukrainian home textile brand «L».

Understanding and forecasting Customer Lifetime Value (CLV) is becoming increasingly important in today's competitive e-commerce environment, particularly in the home textiles sector. For the company «L», analyzing the factors that influence CLV is highly relevant. This analysis will help identify the most valuable customers. In the future, the results of this study will help develop better marketing strategies, improve categories or specific products, and measure and manage customer loyalty, which can reduce marketing costs.

The main question to be analyzed is: what factors, such as characteristics of the first purchase, frequency of purchases, average order value, product categories purchased affect the predicted customer lifetime value (CLV) for the company «L»?

Understanding the factors that influence CLV will help the company «L» identify the customer's most valuable segments to the business in the long term. It will enable the company to focus efforts on retaining and developing relationships with these customers, which will help growth, especially in an environment where attracting new customers can be significantly more expensive than retaining existing ones. Ferrentino et al. (2016) note that CLV models enable companies to allocate resources more effectively and develop targeted marketing strategies.

The research results can be used to enhance the company's marketing efforts, such as developing loyalty programs, increasing purchase frequency and average order value, optimizing the assortment, or improving the overall customer experience. If this research reveals that customers who purchase products from different categories have higher CLV, the company «L» can encourage cross-selling. An analysis of CLV and the factors that influence it will provide the company «L» with recommendations on maximizing the long-term profit from each customer.

This research combines two of the most important dimensions of business: marketing, primarily in terms of loyalty management, customer acquisition, and behavior analysis, and finance, by measuring the value of a customer in monetary terms. This approach enables us to view the customer base as a valuable asset of the company.

Thus, research on factors influencing CLV will help the company «L» gain essential knowledge to make strategic decisions. This knowledge will help increase marketing effectiveness, improve the customer experience, and ultimately enhance profitability.

CHAPTER 2. INDUSTRY OVERVIEW AND RELATED STUDIES

Company «L» is a Ukrainian brand founded in 2018 that specializes in solid-color home textiles made from natural fabrics such as cotton, linen, and muslin. The brand mainly sells bedding, home clothes, blankets, pillows, and throws. The assortment also includes towels, curtains, aprons, napkins, and bedspreads. The brand considers its advantages as high-quality materials, an unconditional 30-day return guarantee, fast next-day delivery, and the ability to produce individual orders. The brand primarily sells its products through its website and social media.

To fully understand the context of the facts affecting CLV for «L», it is necessary to consider the specifics of the home textiles market in Ukraine, especially its online segment, and analyze existing scientific works devoted to CLV and consumer behavior in e-commerce.

The textile market, particularly home textiles and sleepwear, is an important component of the Ukrainian commodity market. In this section, we will discuss two key components of the Ukrainian textile market: suppliers (manufacturers) and buyers. Ukrainian consumers of home textiles are becoming increasingly demanding. They are looking not only for aesthetically appealing products but also for practical, durable, and safe products. There is a growing interest in products made from natural and environmentally friendly materials, as well as in innovative fabrics with improved properties (e.g., thermoregulating, hypoallergenic). Online purchases of home textiles are becoming increasingly common, and consumers expect a convenient ordering process, fast delivery, and high-quality service (Holovenko et al., 2024).

In 2024, 56% of purchases are made offline, and 38% online. The average check for offline purchases is UAH 3954 and UAH 3516 for online purchases (Deloitte, 2024). Men made purchases more often during the month (0.7 times) than women (0.5 times), spending 7% more than they did in 2023.

The most active group of buyers is people aged 18-27, who purchase furniture and home goods in traditional stores on average 1.7 times a month and spend almost UAH 1,500 more than the average Ukrainian.

Let us consider purchases in online stores to which «L» belongs. The share of Ukrainians who purchase furniture and household goods online is 38%, which is almost two percentage points less than in 2023. However, the frequency of such purchases has increased on average from once per quarter (2023) to once every two months (2024).

As in offline stores, men are the most active buyers in this category of goods, typically making 3-4 purchases per year and spending, on average, 11% more than women on each purchase. The decrease in the frequency of purchases and the average cost per purchase correlate with the increase in the respondent's age.

Residents of small towns reduced their expenses by 19% (to 3017 UAH per purchase), while residents of medium and large cities increased their expenses by 4% and 8%, respectively. Compared to 2023, the frequency of purchasing furniture and household goods in online stores increased among employed Ukrainians (75% to 0.7 times a month) and the temporarily unemployed (50% to 0.3 times a month). Over 60% of Ukrainians who purchased furniture and home goods in 2024 preferred traditional stores, while only 18% preferred online stores, and 22% shopped equally in stores of both formats (Deloitte, 2024).

When considering the impact of the war on the manufacturers' market, the full-scale invasion had a particular, albeit minor, effect on the market structure. However, the number of new entrepreneurs in 2023 skyrocketed. The number of enterprises that ceased their activities increased from 2% to 10% in two years. In 2022, the increase in registered SPDs amounted to -1% of entities; most closures concerned individual entrepreneurs. However, 2023 became a year of rapid growth of new entrepreneurs in the target industries.

The increase amounted to +22% of entities, most of whom are individual entrepreneurs, but 1% of new legal entities also appeared.

In dynamics, the structure of prominent leaders has undergone minor changes, with only the TEMP-3000 company remaining in the top three in terms of revenue from 2022 to 2023. However, in 2021, the company was not even in the top 50. This company is not included in the comparative table in this analysis because it specializes mainly in military ammunition and actively cooperates with the state, unlike the work of other manufacturers in the B2B or B2C segments. This company also primarily produces military products and workwear, but the list mentions coats, jackets, and raincoats, without including home textiles.

All identified leaders of the light industry market export their products. Market leaders offer a relatively wide range of products, covering the production of textiles, including knitwear, silk, wool, raincoat fabric, calico, leather and leather products, footwear, workwear, women's and men's clothing, among others.

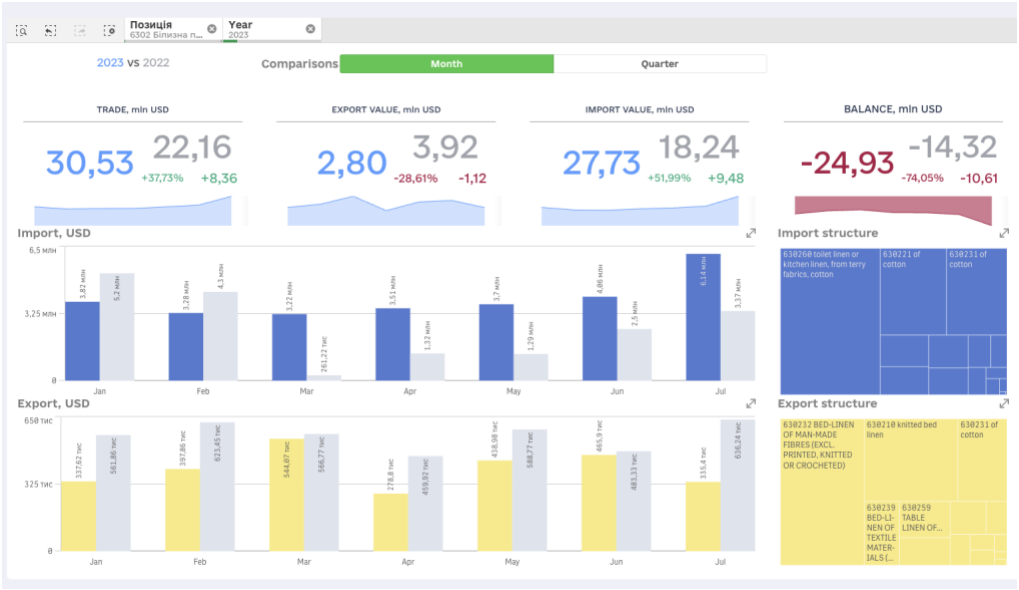
Usually, leaders extremely rarely combine light industry with other industries in their work: some companies focus entirely on the production of textiles, that is, raw materials, while others produce clothing exclusively. By the end of 2023, a significant portion of the ranking will be comprised of manufacturers of workwear, including military, medical, tactical, and firefighting products. Additionally, individual market leaders produce carpets, leather goods, and specialized bags for carrying hazardous materials. Most leaders, in terms of revenue, typically manage only one brand.

The biggest challenges for producers remain full-scale war (including shelling and economic instability), import dependence, limited resources, and a lack of human capital. The market mainly depends on imported raw materials — only 10%- 15% of raw material needs are met by domestic production, and the rest are imported from abroad. The same applies to equipment - it's expensive for a domestic manufacturer.

In 2023, China accounted for 34% of total imports, valued at $1,073.71 million USD. In second place is Turkey (17%) and 543.22 million USD. Next are Poland, Germany, Bangladesh, and Italy. One of the opportunities for Ukrainian manufacturers is to export to other countries. According to experts, with the beginning of the full-scale invasion, the inscription "Made in Ukraine" has become a synonym for instability and negatively affects potential customers' desire to choose a Ukrainian manufacturer. In other words, the long war has negatively affected the brand image under the "Ukrainian" label.

To reduce risks, foreign partners may offer to reduce the price, cancel prepayment, or offer other concessions. It is also worth noting that logistical difficulties arise due to closed ports or blocked borders (Fama & Ukrlegprom, 2024).

Figure 1. Export and import of bed linen in Ukraine.

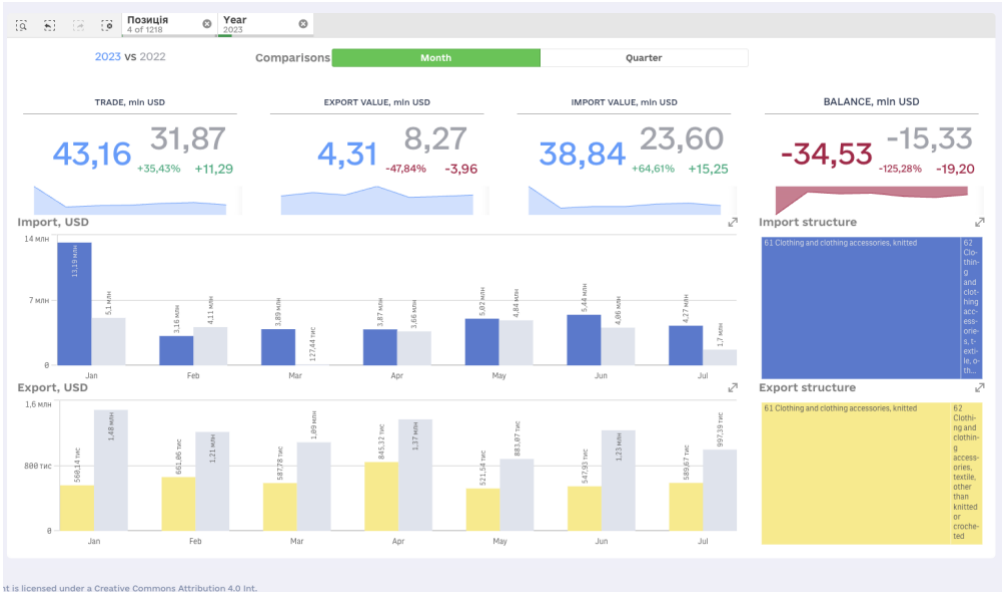


Source: State Customs Service of Ukraine

If we talk about bed linen, the company «L» main product, in 2023, Ukraine exported products worth 2.8 million US dollars while importing 27.73 million US dollars. In homeware (pajamas and suits), exports and imports are distributed as follows: 4.31

million USD were exported, and 38.84 million USD were imported. (State Customs Service of Ukraine).

Figure 2. Export and import of pajamas and loungewear



Source: State Customs Service of Ukraine

According to OpenDataBot, the company «L» competitors occupy significantly higher positions but usually sell cheaper products and focus on wide B2B distribution.

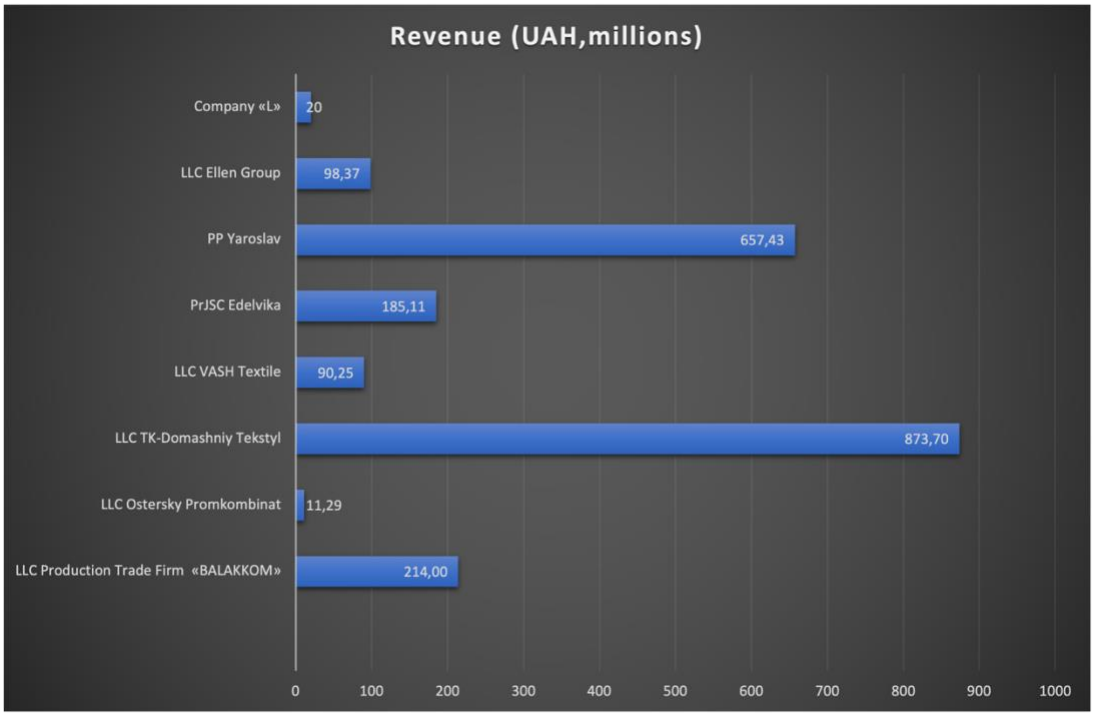
Table 1. The largest players in the textile market, and the company «L» among them, in 2024

Name	Brands	Revenue (UAH, millions)	Assets (UAH, millions)	Liabilities (UAH, millions)	Employees
LLC Production Trade Firm «BALAKKOM»	TEP, Balakkom	214,00	239, 66	17	192
LLC Ostersky Promkombinat		11,29	8,64	8,36	22
LLC TK-Domashniy Tekstyl	Home Line	873,70	789,04	431,25	186

LLC VASH Textile	Zastelli	90,25	113	24,78	24
PrJSC Edelvika		185,11	292,34	114,31	214
PP Yaroslav	Yaroslav	657,43	454,07	128,36	760
LLC Ellen Group		98,37	69,73	7,05	126
Company «L»		**20,08**	**5,78**	**1,04**	**10**

Source: OpenDataBot

Figure 3. Graphical distribution of textile manufacturers in Ukraine



Source: OpenDataBot, provided by the company in the industry

The concept of CLV has been actively researched in the academic literature over the past two decades. Of particular interest are works related to CLV's calculation, forecasting, and use in e-commerce and retail.

The scientific literature contains various methodologies for calculating and forecasting CLV. This study plans to use historical CLV and build a model to predict future CLV using regression analysis.

Customer Lifetime Value (CLV) is based on the net present value (NPV) analysis. In analogy to financial assets, where NPV is the sum of discounted future cash flows from an asset, CLV is defined as the NPV of future profits a customer generates (Zhang et al., 2010). A common approach assumes that the duration of the customer relationship is known, and based on this, the discounted cash flow for the relevant period is calculated (Berger & Nasr, 1998).

The standard simplified formulas for calculating CLV, which will be used in this research project, are $\mathrm{CLV} = \frac{mr}{(1+i-r)}$ where m is gross margins, r is retention rates, and i is the discount rate to account for money's time value. This formula, as noted by Zhang et al. (2010), is based on the assumption of constant margins and retention rates over an infinite time horizon, simplifying the calculations. Regression analysis allows for identifying statistically significant factors that influence CLV, considering CLV as the dependent variable and various customer characteristics and their behavior as independent variables.

RFM analysis (Recency, Frequency, Monetary) is a popular method of segmenting customers based on the time of the last purchase (Recency), the total frequency of purchases (Frequency), and the total amount spent (Monetary). Zhang et al. (2010) mention RFM as one type of scoring model, and Jašek et al. (2014) note that RFM serves well as an introductory tool for customer segmentation. The results of RFM analysis can serve as a baseline for evaluating the effectiveness of more complex models.

Borle et al. (2008) analyze the modeling and application of CLV specifically in online retail. They compare the predictive performance of different CLV models, including models based on Pareto/NBD, Markov chains and vector autoregression, on large datasets from online stores. Their research emphasizes the importance of selecting an appropriate model based on the characteristics of the data and business objectives, and also highlights the potential of utilizing non-financial data.

It is worth mentioning RFM analysis, which Fader et al. (2005) also refer to as a method of segmenting customers based on the age of the last purchase, frequency of purchases, and total spending. RFM analysis is often used as a starting point for estimating customer value and can serve as a benchmark for more complex models.

This research will use regression analysis to test the customer lifetime value (CLV) hypotheses. This method will help identify factors that significantly impact CLV. The dependent variable will be the historical or projected CLV. In contrast, the independent variables will include various customer characteristics and behaviors, such as demographics, purchase history, and promotional codes.

Previous studies have examined several factors that influence CLV. For example, first purchase characteristics (cost of the first product) or the products purchased can signal the future potential of the customer. Purchase frequency and average purchase amount can also influence CLV — customers who buy more frequently and spend more per transaction tend to have higher CLV (Pepe, 2011). Customers who buy products from different categories may be more engaged and loyal, positively affecting their CLV. (Werner et al. 2008). The impact of promo (discount codes) is also worth mentioning. Promo codes can stimulate purchases; conversely, they can attract customers only focused on discounts. (Al-Hammouri et al. 2022).

Age, gender, and location (demographic data) can correlate with purchasing power and preferences (Bauer and Jannach, 2021). The channel through which a customer came (e.g., organic search, paid advertising, social media) can influence their subsequent behavior and CLV (Villanueva et al., 2008). This research will build on existing studies, adapting them to the specifics of the Ukrainian home textile market and the company's existing data.

CHAPTER 3. METHODOLOGY

The methodology of this study aims to quantify the CLV of the company «L» customers and identify key factors influencing it. To achieve this goal, a combination of approaches will be used, including calculating CLV and building a regression model to analyze factors that influence CLV. The research will test the following hypotheses:

H1: Customers whose first purchase included products from a higher price category have higher CLV.

H2: Higher purchase frequency during the first 6 months positively correlates with overall CLV.

H3: Customers who purchase products from different categories have higher CLV than those who buy only from one category.

H4: Shorter time to second purchase is positively correlated with higher overall CLV.

For each customer in the «L» database, a CLV will be calculated, reflecting the customer's present value discounted to the present based on their past interactions with the company. It is planned to use a simplified CLV formula that is widely used in practice and academic research under non-contractual relationships and assumes constant margins and retention rates (Zhang et al., 2010; Gupta & Lehmann, 2005): $\mathrm{CLV} = \frac{mr}{(1+i-r)}$

Hereinafter, the CLV obtained using this formula will be referred to as **CLV_Simple**.

The main components of the formula are:

m (gross margin) – average gross margin from a customer since 2018. The company «L» has been operating since 2018 and aims to use the most up-to-date data. However, this is a home textile sector, and the company's main product is bed linen. It is not known how often customers buy «L» products in the case of repeat purchases. Therefore, we will take data for 7 years, namely from January 1, 2018, to August 28, 2025. The *m* will be calculated

as the product of the average revenue from a customer for the period by the average gross margin ratio for the products. Average revenue will be determined based on the customer's transaction history. The average order value multiplied by the purchase frequency over the period will be used. The gross margin ratio will be taken from the company's financial statements.

Customer retention rate r reflects the likelihood that a customer will continue to buy from company «L» in the next period. It will be calculated based on an analysis of repeat customer purchases over a time interval. When calculating this simplified heuristic indicator CLV_Simple, two methodological adjustments were necessary. First, to avoid the problem of division by zero when calculating the average annual cost for customers with a single purchase, the concept of a "minimum effective life cycle" (MinLifeSpanInDays) was introduced, set at 326 days. This represents the 75th percentile of the time between repeat purchases of customers, calculated on the Power BI side. Second, since the CLV_Simple requires annual indicators, the observed share of active customers calculated for a 661-day window was statistically converted into an equivalent yearly retention rate. To classify customers as "active" and "inactive", a parameter called the Churn Window is 661 days, which corresponds to the 90th percentile of the Time Between Purchases (TBP). If the customer is lost (CHURN_WINDOW_DAYS since the last purchase) → CLV_Simple = 0.

$$r_{year} = 1 - (1 - r_{observed})^{\frac{365.25}{661}} \quad (1)$$

To determine the discount rate (*i*) in the models, the weighted average cost of capital (WACC) was chosen. This approach can be justified by the fact that it considers the

customer base as an asset of the company. This equates the value of cash flows from customers to the minimum return that the company must generate on all its capital.

It is worth noting that using WACC as a discount rate for CLV is based on several key assumptions. It assumes that the risk associated with cash flows from the average customer is equal to the average risk of the entire company's operations. In practice, cash flows from new customers may be riskier than those from loyal customers.

The probabilistic model Pareto/NBD model will also be used for comparison. Pareto/NBD (Negative Binomial Distribution) framework proposed by Schmittlein, Morrison, and Colombo (1987). This is one of the most common models, suitable for analyzing customer bases in non-contractual settings, where customers can make purchases at any time and their churn is not directly observable.

This model is also based on several key assumptions about the purchasing process and the customer «lifecycle». While a customer is «active» (alive), the number of transactions they have left is described by a Poisson process with individual purchase intensity λ. Purchases occur randomly over time with some average frequency unique to each customer. After any transaction, a customer can become «inactive» with probability p. The time during which a customer remains active is described by an exponential distribution with a "mortality" parameter μ.

The model takes into account that all customers are different. Therefore, their purchase intensity (λ) and the probability of churn (μ) are distributed across the entire customer base according to a gamma distribution. The purchase intensity distribution (λ) has parameters of the shape r and scale α. The probability of churn (μ) has parameters of the shape s and scale β.

Due to these assumptions, the model adapts to real data, where some customers make frequent purchases and remain active for a long time, while others make infrequent

purchases or leave quickly. All calculations CLV Pareto/NBD (henceforth CLV_PNBD) will be done using the package CLVTool for R Studio.

Table 2. Comparison of the CLV models in research

CLV_Simple	**CLV_PNBD**
Simplified Heuristic CLV (CLV_Simple): Calculated using the classic formula with an infinite horizon. The key feature is that the annual retention rate (r_RetentionRate) is calculated based on the proportion of "active" customers at the time of the data cut. For customers defined as "inactive" (churned), CLV_Simple is set to zero.	Using the R package CLVTools, a probabilistic Pareto/NBD (PNBD) model is built. The data are divided into training (75%) and validation (25%) periods.

After calculating both CLV for each customer, the next step will be to build a model to predict factors that affect it. For this purpose, regression analysis will be employed, specifically multiple linear regression. In this case, the dependent variable will be the calculated CLV (or its logarithm, if the distribution is highly skewed) for each customer.

The independent variables will be factors obtained from the «L» customer dataset that can affect CLV. For the first hypothesis, these will be the cost of the first purchase, the number of products in the first purchase, and the category of products in the first purchase.

To test Hypotheses H2 and H4, the independent variables will be the number of purchases in the first 6 months, the total frequency of purchases, and the average time between purchases, especially between the first and second.

To test Hypothesis H3, the independent variable will be the category of purchased goods — the number of unique categories from which the customer made purchases.

Model for predicting log (CLV_PNBD):

$$log(\text{CLV}_{\text{PNBD}} + 1) = \beta_0 + \beta_1 \cdot \text{FirstPurchaseAmount} + \beta_2 \cdot \text{PurchasesInFirst6Month} + \beta_3 \cdot \text{UniqueCategoriesCount} + \beta_4 \cdot \text{FirstOrderYear}_c + \beta_5 \cdot \text{Gender}_{\text{male}} + \beta_6 \cdot \text{OrderCount} + \sum_{j=1}^{k-1} \gamma_j \cdot \text{CityDummy}_j + \varepsilon \quad (2)$$

Model for predicting log (CLV_Simple):

$$\log(\text{CLV}_{\text{Simple}} + 1) = \beta_0^{(S)} + \beta_1^{(S)} \cdot \text{FirstPurchaseAmount} + \beta_2^{(S)} \cdot \text{PurchasesInFirst6Months} + \beta_3^{(S)} \cdot \text{UniqueCategoriesCount} + \beta_4^{(S)} \cdot \text{FirstOrderYear}_c + \beta_5^{(S)} \cdot \text{Gender}_{\text{male}} + \beta_6^{(S)} \cdot \text{OrderCount} + \sum_{j=1}^{k-1} \beta_{7,j}^{(S)} \cdot \text{CityDummy}_j + \varepsilon \quad (3)$$

Time to Second Purchase was not tested in PNBD because Pareto/NBD is a stochastic purchase frequency model.

It works with "recency–frequency–monetary value" (RFM) data, rather than individual time lags between purchases, and estimates the parameters λ (purchase frequency) and p (customer "death" probability) at the population level using the full transaction history.

TimeToSecondPurchase is just one time interval that is not included in the Pareto/NBD parameterization. There is no direct API in CLVTools to include this variable in a PNBD regression; pnbd() estimates parameters without covariates. There are other functions for regressions with covariates (pnbdStaticCov, pnbdDynamicCov), but they require additional data and separate modeling, which would complicate this methodology.

In the final version, a comparable model was made without these variables so that the comparison of PNBD vs Simple CLV was correct (same set of observations).

Cross-Validation and Model Stability

To ensure robust estimation and avoid overfitting of the models, all regression models were estimated using an 80/20 validation scheme (initial value = 42). As mentioned earlier, the Pareto/NBD model used a time-splitting approach—the first 75% of the observation period was used to estimate the model, and the remaining 25% was used as a waiting window for out-of-sample calibration testing as required by the model.

Also, 5-fold cross-validation (three replicates) was performed on the regression models to assess the variability of RMSE and MAE across random folds.

The stability of the model was further tested by comparing the sign and magnitude of key coefficients (Order Count, Unique Categories, $\text{FirstOrderYear}_{(C)}$) across folds. All models used HC1-robust standard errors to reduce heteroscedasticity bias.

Software and Tools

Data processing and analysis were conducted using Power BI. Regression analysis regression analysis was performed in RStudio (version 2024.12.1+563) with CLVTool package.

CHAPTER 4. DATA

The study will use 2 datasets from the company «L»:

1) Transactions. Includes information about customer id, order date (OrderDate), and purchase amount (Order Amount). This data will be used to calculate CLV using the Pareto/NBD model.

2) Compiled dataset that will include calculated metrics.

The transactions dataset used in this study is obtained from the company's CRM, covering the period from January 1, 2018, to August 28, 2025. It contains records of 18,502 orders and 12,058 customers who made purchases during that time. The data collected by company «L» includes the following information about customers.

- Transaction history (dates, amounts, purchased products).
- Demographic data — city, gender

Table 3. Descriptive Statistics of transactions data

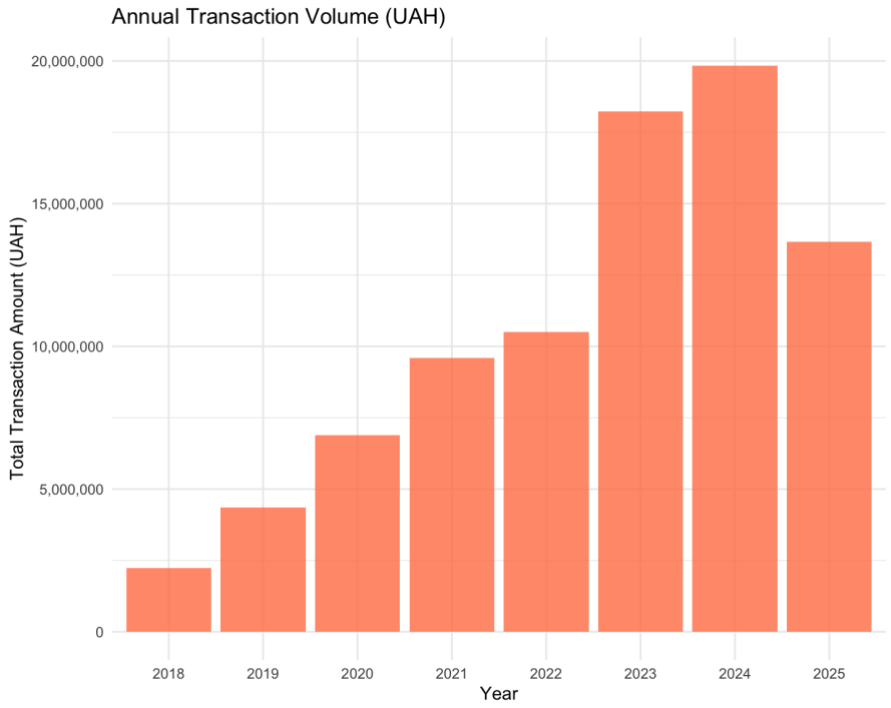
Descriptive Statistics: Individual Transactions

Statistic	N	Mean	St. Dev.	Min	Max
OrderAmount	18,502	4,626.94	4,096.82	136.00	264,600.00

Table 4. Descriptive Statistics — compiled dataset, customer-level metrics

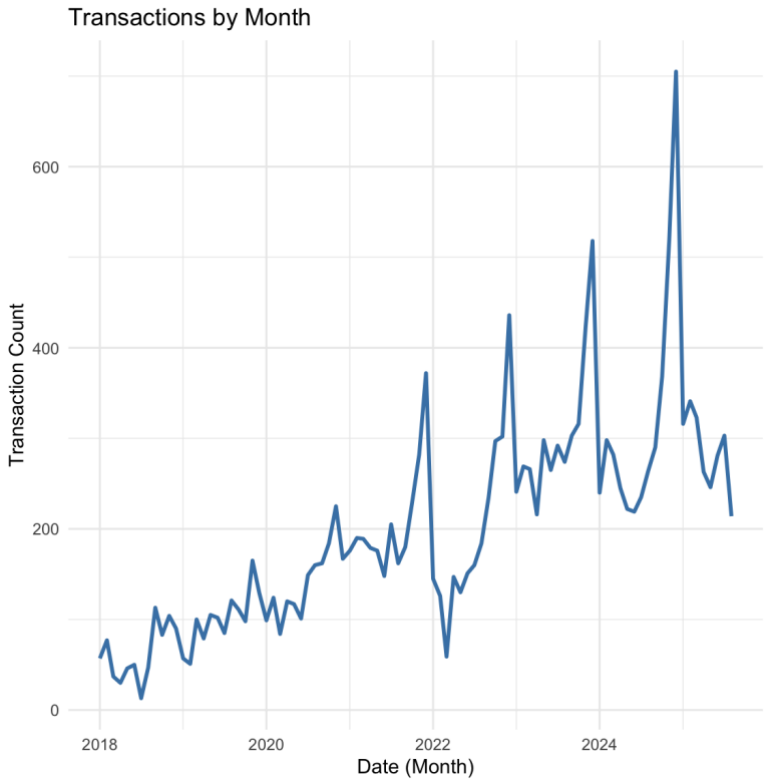
Statistic	N	Mean	St. Dev.	Min	Max
TotalSpend (UAH)	12,058	7,097.62	8,277.92	136.00	264,600.00
OrderCount	12,058	1.54	1.16	1	17
FirstPurchaseAmount (UAH)	12,054	4,562.56	4,238.77	0.01	264,600.00
TimeToSecondPurchase_days	3,476	250.27	349.90	1	2,526
PurchasesInFirst6Months	12,058	1.23	0.56	1	10
UniqueCategoriesCount	12,058	1.33	0.61	1	5
StdDev_TimeBetweenPurchases (days)	1,415	235.40	221.95	0.00	1,451.69

Figure 4. Total revenue 2018- 2025 (August 28)



Source: Own presentation based on transactions data

Figure 5. Orders count 2018- 2025 (August 28).



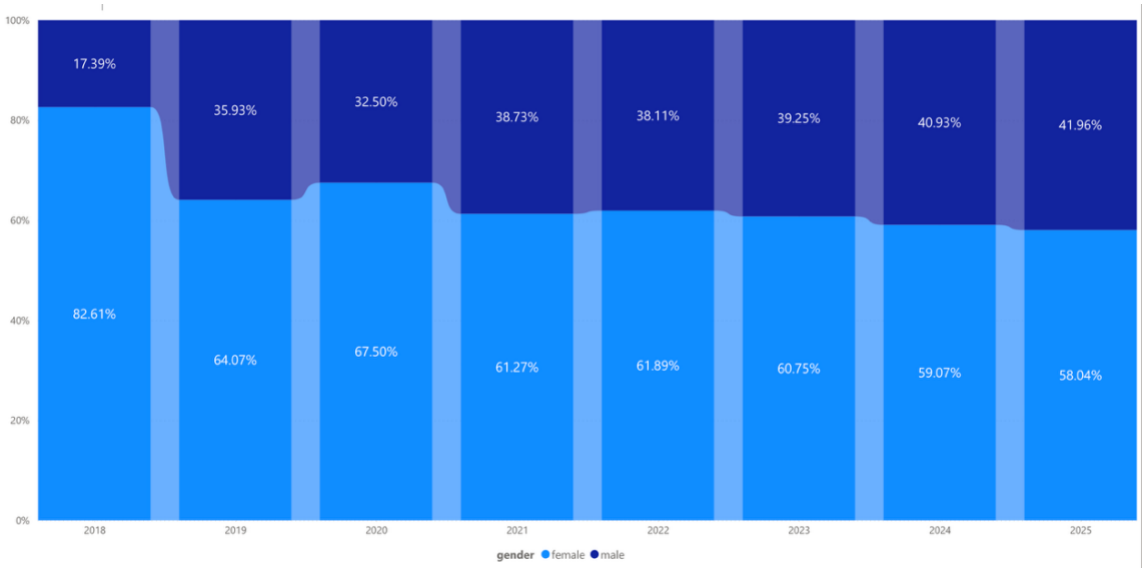
Source: Own presentation based on transactions data

Standardization of city names for correct geographical segmentation was primarily done manually. Cities were displayed in chronological order in relation to one customer. It was found that customers change their place of residence, and the same customer can have up to five cities in their order history. Classification of products by category (bed linen, home clothes, etc.) was carried out to test hypothesis H3.

Calculation of new indicators for each customer, such as purchase frequency, time between the first and second purchase, and number of categories in orders, was done via Power BI.

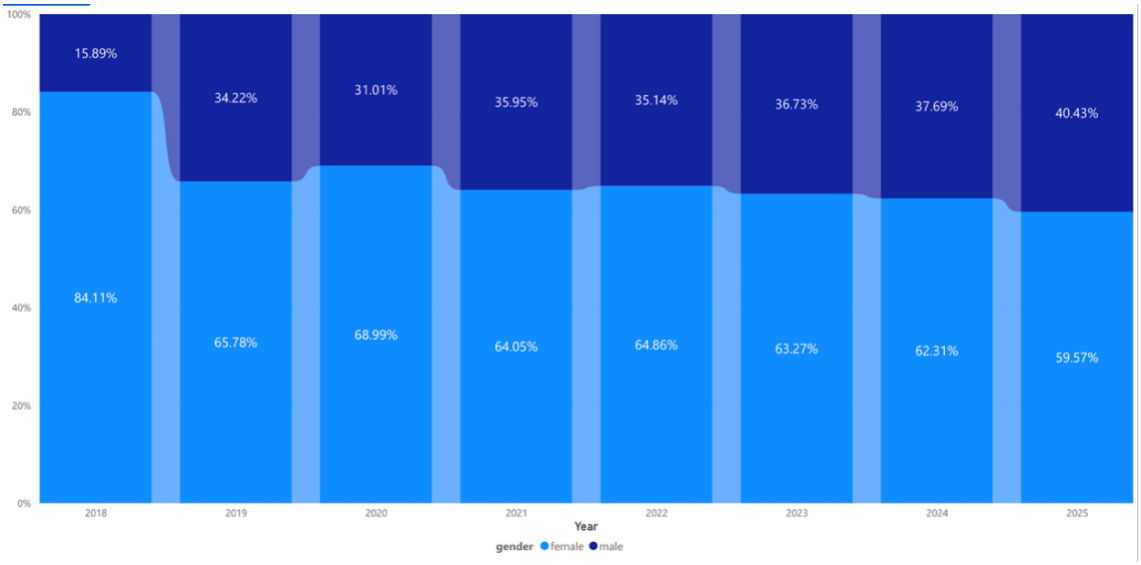
As we can see, the average for orders is 4626 UAH. The number of orders from one customer is from 1 to 17 (average is 1.54). The largest cities of order now are Kyiv, Kharkiv, Dnipro, Odesa, and Lviv.

Figure 6. Revenue by gender



Source: Author's calculations based on Power BI data

Figure 7. Orders count by gender



Source: Author's calculations based on Power BI data

The Figure 6 show that the share of men is increasing, while the share of women is decreasing.

Figure 8. Average order value by gender (quarterly)

Source: Author's calculations based on Power BI data

Average order value of a male client is historically larger than that of a female client (in some periods they overlap). These data are completely consistent with the findings regarding the male audience in the Deloitte, 2024 study.

Table 5. Distribution of customers by number of orders

OrderCountBin	Sum of NumberOfCustomers	Sum of Revenue	Sum of PercentOfCustomers	Sum of PercentOfOrders	Sum of PercentOfRevenue
1	8549	37,508,329.68	70.86%	46.09%	43.80%
2	2088	20,273,747.79	17.31%	22.51%	23.68%
3	722	10,241,739.46	5.98%	11.68%	11.96%
4	356	6,761,638.95	2.95%	7.68%	7.90%
5	161	3,915,018.00	1.33%	4.34%	4.57%
6	75	2,015,935.80	0.62%	2.43%	2.35%
7	43	1,511,518.20	0.36%	1.62%	1.77%
8	27	1,066,526.62	0.22%	1.16%	1.25%
9	15	821,210.50	0.12%	0.73%	0.96%
10	11	422,532.00	0.09%	0.59%	0.49%
12	6	279,535.01	0.05%	0.39%	0.33%
11	4	243,370.20	0.03%	0.24%	0.28%
13	3	200,058.00	0.02%	0.21%	0.23%
14	1	68,571.00	0.01%	0.08%	0.08%
15	1	40,599.00	0.01%	0.08%	0.05%
16	1	88,465.00	0.01%	0.09%	0.10%
17	1	171,449.35	0.01%	0.09%	0.20%
Total	**12064**	**85,630,244.56**	**100.00%**	**100.00%**	**100.00%**

Source: Author's calculations based on Power BI data

The biggest problem with the company «L» customer base is that 70.86% of all buyers have made only one purchase since 2018. This is 46.09% of orders and 43.8% of all revenue over the observation period.

Table 6. Variables from the dataset used in calculations

Client_Id	for comparison with data from the previous dataset	
TotalSpend	total client costs for the entire time	
OrderCount	the number of orders the customer placed	
AOV	Average order value	
FirstOrderDate	information about the date of the first order placed by the customer	

LastOrderDate	date of the customer's last order. If there was only one order, it would coincide with the date of the first order	
FirstPurchaseAmount	The amount of the first purchase. For a customer with one order, FirstPurchaseAmount=AOV= TotalSpend	For H1
TimeToSecondPurchase_days	shows the time until the customer's second purchase in days	For H4
PurchasesInFirst6Months	shows how many purchases the customer made in the first 6 months	For H2
UniqueCategoriesCount	counts all categories that the customer purchased.	For H3
FirstPurchase_Category	information about which first category (or categories) the client chose.	
FirstOrderYear, YearOfSecondPurchase	include information about the years of the first and second purchase (if there was no second purchase) YearOfSecondPurchase is not populated.	To answer whether the company is attracting more valuable customers now
Gender	client gender, male, female, or unknown	Does gender affect CLV?

Customer_City_Journey	cities that the customer specified for delivery throughout the entire time.	Does City affect CLV?

The company's products are divided into categories as follows:

Bedding	bed linen, linen set, pillowcases, sheets, duvet covers
Sleep Accessories	pillows, blankets, throws, bedspreads, mattress toppers
Home Clothing	pajamas, dresses (including dress shirts), shirts, pants, t-shirts, shorts, bathrobes
Other Home Textiles	runners, towels, curtains, aprons, napkins, sleep masks
Gift Certificates	gift certificates

Table 7. Time Between Purchases in Categories

ProductCategory	TBP_Mean_by_Category	TBP_Median_by_Category	TBP_90th_Percentile_by_Category
Bedding	252.56	117.00	699.20
Gift Certificates	270.22	137.50	765.50
Home Clothing	235.50	108.00	639.80
Other	179.80	73.00	521.40
Other Home Textiles	293.74	159.00	761.20
Sleep Accessories	213.18	93.00	574.50
Total	**239.72**	**106.00**	**661.00**

The median time between purchases in different categories ranges from 73 to 159 days. The distributions are skewed to the right, with a long tail of slow repeats, resulting in a total 90th percentile of 661 days.

The fastest customer return cycles were found in the "Other" and "Sleep Accessories" categories, with medians of 73 and 93 days. Products in these categories

(which are pillows, throws, and diffusers, which the company sold through 2023) are less expensive and require more frequent replacement than bedding.

The longest return cycles were found in the "Other Home Textiles" and "Gift Certificates" categories, with medians of 159 and 137.5 days. Textiles, such as curtains or tablecloths, are purchased infrequently, while certificates are often situational, typically one-time purchases, usually made for holidays. The company's key categories, "Bedding" and "Homewear" fall in the middle, with medians of 117 and 108 days.

4.3 WACC Calculation

After determination of the total cost of capital (V) and the share of each of its components (equity E and debt D).

Equity of the company (E): 4 099 071 UAH

Debt capital (D): 2 424 167 UAH

Total capital (V = E + D): 4 099 071 + 2 424 167 = 6 523 238 UAH

Equity ratio (E/V) 4099071/ 6523238 = 0,6284 or 62,84%

Debt ratio (D/V): 2424167/ 6523238 = 0,3716 or 37,16%

The weighted average interest rate on your long-term liabilities for company «L»:

- Debt 1: 460000 UAH 18% per year
- Debt 2: 1964167 UAH 2% 24% per year

$R_{d=\left(\frac{460000}{2424167}*18\%\right)+\left(\frac{1964167}{2424167}*24\%\right)}$=22,86%

Calculation of the cost of equity using CAPM: $R_e = R_f + \beta_L * (ERP)$

R_f =16,18% (Weighted average yield on long-term Ukrainian government bonds as of August 2025)

ERP is determined by 21,96% according to Aswath Damodaran, Professor of Finance at the Stern School of Business at New York University (Damodaran, 2025), as well as the $B_L = 1{,}48$, $B_U = 1$

This is the average risk score for the company «L» industries, taken from A. Damodaran's data, "Retail (General)"=1, Furn/Home Furnishings": B_U=1.00, Average B_U= (1+1)/2 = 1

Calculating the debt-to-equity ratio (D/E): $\frac{D}{E}=\frac{2424167}{4099071}$=0,59

$B_L = B_U * \left(1 + (1-t) * \frac{D}{E}\right)$= 1 * (1+(1-0,18) * 0,59) = 1,48

Where t=0,18 (18% tax rate in Ukraine)

This reflects the additional risk that business debt creates.

R_e=16.18%+1.48*21.96%= 48,68%

WACC=$(\frac{E}{V} * R_e) + (\frac{D}{V} * R_d * (1-t))$

WACC = (62,84% * 48,68%) + (37,16% * 22, 86%) *(1-0,18) = 37,55%

This study utilizes the company «L»'s current capital structure to calculate the weighted average cost of capital (WACC). This study assumes that the company, being in the growth stage, will continue to maintain a similar financing policy in the near future, so the current capital structure is expected to remain unchanged.

In similar studies on the topic of CLV, the most common discount rate values are typically 10–20% (with 20% most often reported in Berger & Nasr, Pepe; 15% in Fader et al.; and 10–15% in Borle et al.). Therefore, the CLV was calculated for each customer individually:

i =37,55% (From WACC).

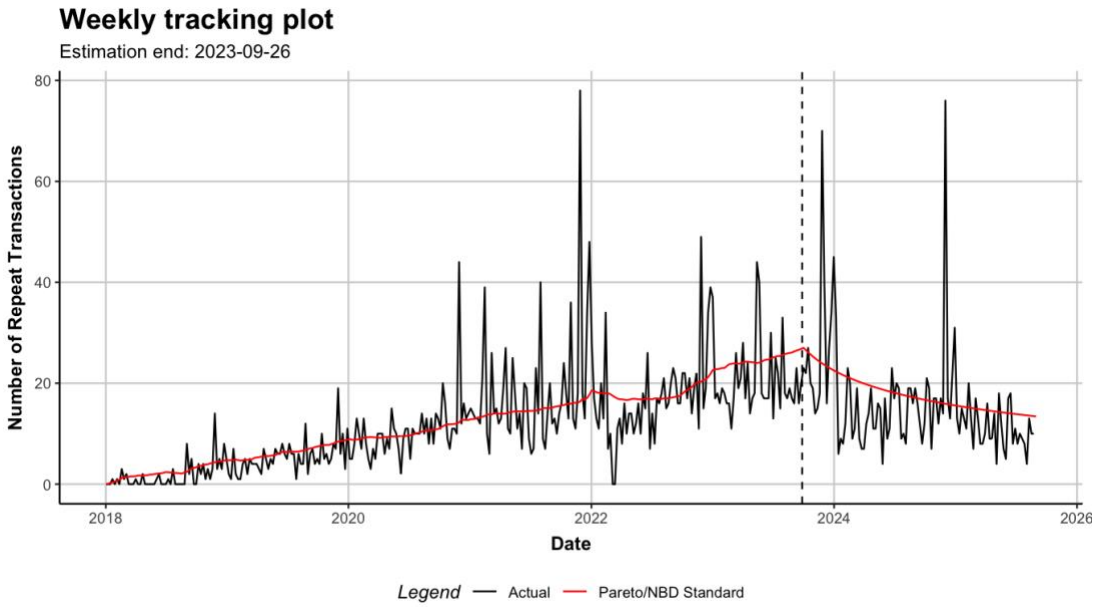
The high WACC reflects elevated market and country risk for Ukraine in 2025.

r (retention rate) was determined based on the churn window, which in days is 661 days (90th percentile of time between purchases)

m(margin) is defined as the average company's marginal profit indicator (72.5% of revenue).

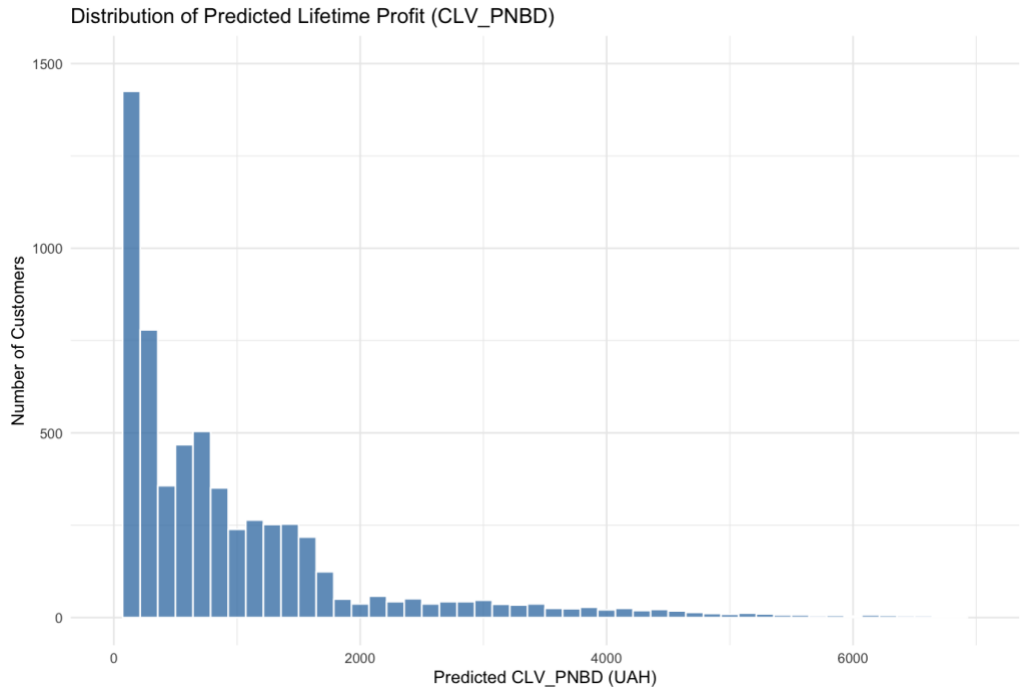
The CLV_PNBD cohort includes data up to and including 2023, since the model requires 75% of the data for training, and 25% for forecasting. Clients were divided into cohorts by year of engagement. The CLV_PNBD cohort includes data up to and including 2023, as the model requires 75% of the data for training and 25% for forecasting.

Figure 9. Weekly tracking plot Pareto/NBD



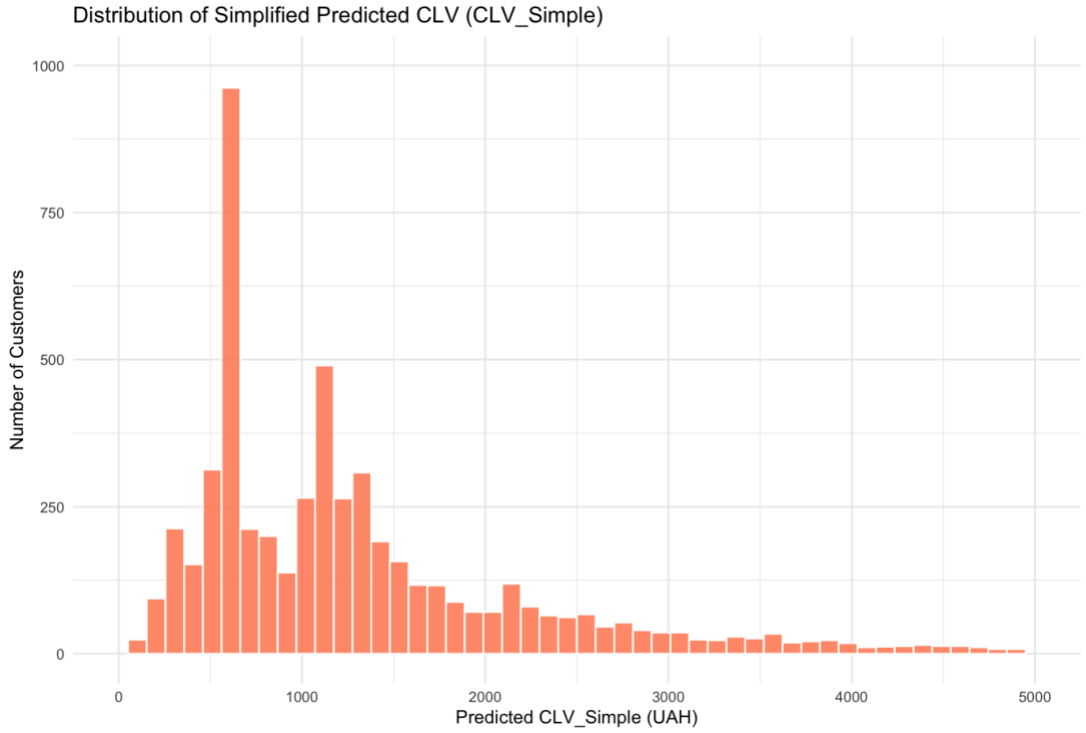
Source: Own presentation based on Pareto/NBD model

Figure 10. Distribution of CLV (Predicted Pareto/NBD model)



Source: Own presentation based on Pareto/NBD model

Figure 11. Distribution of CLV (CLV_Simple model)



Source: Own presentation based on Pareto/NBD model

CHAPTER 5. RESULTS

The simulation results indicate a significant difference in the predictability of the two approaches to calculating Customer Lifetime Value. The Pareto/NBD model shows a high level of explanatory power ($R^2 \approx 0.733$). This is entirely consistent with previous studies (Fader et al., 2005; Jasek et al., 2019). Low RMSE and MAE values confirm that the predictions are calibrated and close to the actual values.

In contrast, the more academic CLV_Simple, which was built on aggregated revenue and average customer lifetime indicators, has a significantly lower explanatory power ($R^2 \approx 0.424$). This is expected, as the formula $\frac{mr}{(1+i-r)}$ does not take into account individual purchase patterns, but instead averages the indicators for calculation. Even after expanding the model with behavioral variables, when time to second purchase and standard deviation between purchase intervals were added, the improvement is relatively modest ($R^2 \approx 0.489$). Still, it is worth noting that the amount of data is significantly reduced, as customers who have two or more purchases and remain active are fewer in number than in the basic Pareto/NBD and CLV_Simple models. This confirms the importance of using stochastic models (like PNBD) for businesses where repeat purchases significantly affect revenue.

According to Table 10 and Table 11 in Appendix:

1. First Purchase Amount PNBD: $\beta \approx 0.00000$, not significant—the size of the first purchase is not a predictor of future CLV in sample. **Hypothesis H1 is not confirmed**.

2. Purchases in First 6 Months PNBD: $\beta = -0.308^{***}$ and for Simple CLV: $\beta = -1.134^{***}$ The more purchases in the first 6 months, the lower the CLV. **H2 is rejected**.

3. Unique Categories Count PNBD: $\beta = 0.070^{***}$

Customers who purchase in more categories have higher CLV. This behavior suggests a more profound connection with the brand (cross-sell effect). **Hypothesis H3 is supported.**

4. First Order Year (centered) PNBD: $\beta = 0.625^{***}$
The later the customer joined (i.e. closer to 2025), the higher the CLV.

5. Gender (Male) PNBD: $\beta = 0.022$ (insignificant) — the gender of the customer has no statistically significant effect on CLV.
6. Order Count PNBD: $\beta = 0.582^{***}$
The more orders a customer has, the higher the CLV, which is the expected and strongest factor.
7. City Dummies Kyiv: positive and significant in PNBD ($p<0.1$). Customers from Kyiv have a slightly higher CLV, but it is worth considering that, in general, most buyers are from Kyiv. Other cities do not show a statistically significant difference.

Hypothesis H4 tested the effect on Time to Second Purchase and was evaluated only for the Simple CLV (Extended) model; however, the variable did not yield a statistically significant result (0.0004). Hypothesis not confirmed.

Among the most important determinants of CLV in all models were Order Count (the total number of purchases) and FirstOrderYear (the centered year of the first purchase).

Table 8. Interpretation of results for CLV_PNBD

Predictor	β	% Change in CLV	Interpretation
First Purchase Amount	0.00000	0%	No impact

Purchases in First 6 Months	−0.308***	−26.5%	Each additional purchase in the first 6 months → CLV decreases by ~26.5%
Unique Categories Count	0.070***	+7.25%	Each additional category → CLV increases by ~7.25%.
First Order Year (centered)	0.625***	+86.8%	Every year later → CLV increases by ~87% (new customers are more valuable).
Gender (Male)	0.022	+2.2%	Not statistically significant — no real effect.
Order Count	0.582***	+79%	Each additional order → CLV increases by approximately 79%
Kyiv city	0.034*	+3.5%	Customers from Kyiv have a CLV ~3–4% higher.

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. Robust standard errors (HC1)

These indicators have the following impact:

A positive and statistically significant coefficient of year indicates that newer customers have a higher CLV on average. This can be a consequence of business growth, a gradual price increase by the brand, or improved marketing campaigns in later years (for example, in 2024, the company updated its brand strategy). Interestingly, the variable PurchasesInFirst6Months has a negative and statistically significant value in all models (from 1.194*** to 0.310***), which may indicate a "burnout" effect of customers who buy intensively in the first months, or their rapid closure of all needs - in the future, these customers do not remain long-term.

Table 9. Comparison of CLV regression models

Target	Model	R2	Adj_R2	AIC	BIC	RMSE_Test	MAE_Test
CLV_PNBD	PNBD Model (Comparable)	0.7335	0.7330	13,445.021	13,525.555	789.132	360.5742
CLV_Simple	Simple CLV (Comparable)	0.4236	0.4226	25,639.186	25,719.719	4,695.339	231.4923
CLV_Simple	Simple CLV (Extended Features)	0.4954	0.4890	4,562.098	4,630.133	13,141.840	4,226.6813

The comparison shows that the Pareto/NBD model on the comparable sample has higher explanatory power ($R^2 \approx 0.73$) and lower AIC/BIC and errors (RMSE/MAE) than the simple CLV model. Similar figures for CLV_Simple Extended are added to this table; however, it is worth noting that the AIC/BIC and errors are not directly comparable to those of the baseline models due to the different sample and target scales. However, this version of the simple model shows an improvement in R^2 for the subsample of customers with two or more purchases.

Overall, the results confirm that the PNBD model is more flexible and informative for predicting the long-term value of a customer. CLV_Simple is more suitable for use as a basic metric for quick business assessments, but it is not a suitable foundation for more comprehensive evaluations.

To ensure the reliability of the results obtained, the CLV _PNBD model was tested for compliance with the key assumptions of the least squares method. A VIF test was conducted to assess multicollinearity. The results showed that the VIF values for all variables are significantly lower than the threshold value of 5 (or 10), indicating no serious multicollinearity in the model.

A Breusch–Pagan test (bptest) was performed to check for heteroscedasticity. The test revealed the presence of heteroscedasticity ($p < 0.05$). To correct and obtain reliable standard errors and p-values, robust standard errors (HC1) were used in all regression models, as specified in the methodology. Visual analysis of diagnostic plots (Residuals vs.

Fitted and Q-Q Plot) showed that there are some deviations from normality in the "tails" of the distribution. However, considering that the model is based on financial data, the linearity assumptions are met satisfactorily.

5.1 Limitations

The main limitation of this study is the difference in the samples used to calculate the various CLV indicators. The CLV_Simple model is based on the complete purchase history of all customers up to August 28, 2025. In contrast, CLV_PNBD was estimated only for customers who had sufficient purchase history in the estimation window, i.e., up to the split date. This is a standard requirement of CLVTools - all "fresher" customers fall only into the holdout, and for them, the model makes a forecast based on the estimated parameters. This leads to the fact that the regression results for CLV_PNBD reflect the CLV drivers mainly for the "older" customer cohorts that were present at the beginning of the observation period. Such a difference may affect the conclusions, especially if the behavior of new customers (2023+ years old) differs due to changes in marketing strategies, pricing policies, or macroeconomic conditions. Therefore, the results should be interpreted in this context, and future studies should include separate analyses for the latest cohorts or use rolling-window model calibration.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

Based on the CLV analysis and regression analysis of the predictors that influence it, several recommendations can be formulated to increase the value of the customer base. Firstly, the company is recommended to focus on customers with a high volume of orders and incentivize them to place additional orders. The number of orders is the primary driver of CLV. They can be incentivized through repeat purchases, loyalty programs, personalized offers, or increased frequency of communication.

Since the PurchasesInFirst6Months ratio indicates that excessive activity at the start can signal rapid churn, the company is advised to create a "churn-watch" segment and implement proactive measures (reminders, special offers) to retain these customers after the first half of the year. For example, after a customer's second or third purchase within the first six months, automatically include them in the "churn-at-risk" segment and launch an email campaign aimed not at selling, but at attracting customers through storytelling about the brand and fabric care tips.

Given that the more products a customer buys, the higher their CLV, a cross-selling and recommendation strategy can significantly increase customer value throughout their entire customer life. Recommended proactively offering customers who have purchased bed linen a personalized discount on their first purchase of towels or homewear within 30 days of ordering.

The cities in the study did not show a statistically significant effect, but using dummy cities as control variables can help identify local differences in larger samples. Marketing campaigns targeting cities where CLV is lower than average can be further tested.

It is also recommended to move away from simple retrospective metrics such as TotalSpend. It is worth implementing regular monitoring of the customer's PAlive using

the PNBD model. If this indicator decreases, use retention return channels and offer special offers. For example, in CRM, you can set up automatic triggers like "If PAlive (the probability that the customer is still active) drops below 50%, automatically send a personalized 'we miss you' email with a special offer, or a promo code.

In summary, the results of this study confirmed that CLV modeling can serve not only as a measurement tool but also as a support mechanism for the company's marketing decisions. For Company «L», transitioning from descriptive to predictive analytics could be a crucial step toward data-driven customer relationship management.

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APPENDIX

Table 10. Regression results of CLV_Simple model and CLV_PNBD

Table: Comparable Regression Results for log(CLV+1)

	Dependent variable:	
	log(CLV + 1)	
	PNBD Model	Simple CLV Model
	(1)	(2)
First Purchase Amount	0.00000	0.00002
	(0.00000)	(0.00001)
Purchases in First 6 Months	-0.310***	-1.194***
	(0.033)	(0.093)
Unique Categories Count	0.063**	0.306***
	(0.025)	(0.070)
First Order Year (centered)	0.624***	0.365***
	(0.006)	(0.017)
Gender (Male)	0.020	-0.042
	(0.020)	(0.054)
Order Count	0.582***	1.307***
	(0.021)	(0.060)
City: Kyiv	0.034*	0.247***
	(0.020)	(0.058)
City: Lviv	0.043	0.217*
	(0.034)	(0.114)
City: Odesa	-0.023	0.128
	(0.043)	(0.121)
City: Dnipro	0.035	0.134
	(0.058)	(0.132)
Constant	5.181***	-0.322***
	(0.032)	(0.103)
Observations	6,070	6,070

R^2	0.733	0.424
Adjusted R^2	0.733	0.423
Residual Std. Error	0.732	1.998
F Statistic	1,667.526***	445.229***
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 11 Regression results of CLV_Simple Extended

Table: Regression Results for Simple CLV (Extended Features, on 2+ purchasers)

	Dependent variable:
	log(CLV+ 1)
First Purchase Amount	0.0001***
	(0.00002)
Purchases in First 6 Months	-0.837***
	(0.118)
Unique Categories Count	-0.072
	(0.104)
First Order Year (centered)	1.483***
	(0.058)
Gender (Male)	0.111
	(0.181)
Order Count	0.809***
	(0.062)
Time to Second Purchase (days)	0.0004
	(0.0004)
Std Dev Time Between Purchases	0.006***
	(0.0004)
City: Kyiv	0.001
	(0.198)

City: Lviv	0.091
	(0.307)
City: Odesa	-0.069
	(0.413)
City: Dnipro	-0.231
	(0.471)
Constant	0.302
	(0.407)
Observations	953
R^2	0.495
Adjusted R^2	0.489
Residual Std. Error	2.629
F Statistic	76.909***
Note:	*p<0.1; **p<0.05; ***p<0.01