DOI: 10.61954/2616-7107/2024.8.3-6 ISSN 2616-7107

UDC 339.138:004.738.5
JEL: M31, C53, L81

APPROACHES TO MODELLING MARKETING STRATEGIES IN E-COMMERCE

Kostyantyn Afanasyev
Kyiv National Linguistic University,
Kyiv, Ukraine
ORCID iD: 0000-0002-4613-3525

Iryna Hanechko*
State University of Trade and Economics,
Kyiv, Ukraine
ORCID iD: 0000-0002-1918-3164

Oksana Trubei
State University of Trade and Economics,
Kyiv, Ukraine
ORCID iD: 0000-0003-4882-5813

Kateryna Lukhanina
State University of Trade and Economics,
Kyiv, Ukraine
ORCID iD: 0000-0003-3755-638X

*Corresponding author:
Email: i.ganechko@knute.edu.ua

Received: 31/05/2024
Accepted: 25/09/2024

DOI: 10.61954/2616-7107/2024.8.3-6

Introduction. Increasing the efficiency of business activities requires developing a marketing strategy using e-commerce to attract a wide range of customers and maximise the company's income. The key marketing metric for most companies is the customer lifetime value indicator, which is why studying approaches to forecasting this indicator in e-commerce requires special attention, considering the changing business operation environment.

Aim and tasks. The study aims to develop approaches to modelling the marketing strategy of e-commerce enterprises. The tasks are a comparative characterisation of modern marketing planning tools and an empirical analysis of the possibilities of using the BG/NBD model for marketing planning in e-commerce companies, considering the need to implement scenario marketing planning in unstable conditions.

Results. A comparison of the characteristics of the main marketing planning tools was conducted according to features such as content and focus, functional purpose, and planning period, which allows more purposeful use of these tools to solve specific tasks. In order to automatically obtain the required data format for modelling, a Visual Basic program was developed, a forecast of customer behaviour was built, and an indicator of customer transactions was determined for further calculation of customer lifetime value (CLV). During the simulation, four parameters of the BG/NBD model were evaluated, and the maximum value of the logarithmic likelihood function equal to 14460.54 was obtained. The expected number of transactions (forecast time = 26 weeks) was determined for each client from the database. After calculations the information was received, the selected client will make 2.35 transactions during the forecast period of 55-80 weeks. The recommended algorithm for using the BG/NBD model as part of a scenario approach for forecasting the cost of the customer's life cycle allows for more flexible forecasting of digital business revenues and building an optimal marketing strategy.

Conclusions. An empirical study of the possibilities of using the BG/NBD model for marketing planning in e-commerce companies showed that, for the simulation of indicators that affect a company's marketing strategy, it is crucial at the initial stage to convert the database of customer purchases into the input format required for modelling. Using a scenario approach allows e-commerce enterprises to carry out variable marketing planning and reduce risks under growing uncertainty. A well-designed marketing strategy that can be adapted to different business development scenarios enables an e-commerce company to increase its sales.

Keywords: marketing strategy, CLV, NBD-models, GTM-strategy, e-commerce, customer base management.

1. Introduction.

The level of digitalization of business directly depends on the promotion of products or services on the market and the expansion of e-commerce. Online trading allows for more transactions on online platforms, which requires the availability of the necessary digital tools (Morokhova et al., 2023).

E-commerce, in particular, allows existing and newly created enterprises to enter markets and develop and improve business efficiency quickly (Bazaluk et al., 2024). The income growth in e-commerce is due to three factors: the development of the retail market, inflation and the transition from offline to online business.

With global retail growth at 4% and global inflation at just over 5%, the move to online business adds 1-2% to e-commerce growth on average (ECDB, 2024b). According to the ECDB centre (ECDB, 2024a) Ukraine is the 49th largest e-commerce market, with projected revenue of US 4,429.4 million dollars by 2024.

Revenue is expected to show a compound annual growth rate (CAGR 2024-2028) of 6.6%, leading to a projected market volume of US 5,712.4 million dollars by 2028. With an expected growth of 8.9% in 2024, the Ukrainian e-commerce market will contribute to a global growth rate of 10.4% by 2024 (Ukrainian Institute of the Future, 2024).

Hobbies and leisure is the largest segment accounting for Ukrainian e-commerce revenue (26.3%), followed by electronics (20.7%); fashion (16.8%); furniture and home goods (11.8 %); care products (9.4%); DIY (8.9%); groceries (6.2%) (ECDB, 2024a).

Using effective digital commerce solutions by enterprises increases companies' profitability and positively affects the country's GDP (Ukrainian Institute of the Future, 2024). The development of online trade is accompanied by new trends in e-commerce and digital development, which require companies to focus on consumer expectations and their behaviour and, based on this behaviour, forecasts of revenues (De Marco et al., 2021; Harkavenko and Stets, 2022).

2. Literature review.

The problem of achieving business goals using new marketing tools has been discussed previously. The characteristics of the new marketing concept were first formulated and studied by Kotler (et al., 2021), who noted that a business striving for a high level of profitability should consider new technological trends, transform marketing approaches, adapt to change, and move from traditional to digital marketing strategies.

The impact of marketing activities on business value is undeniable. This is confirmed by analysing the quantitative impact of global brands' marketing costs in social networks on the market value of the shares of global companies using an econometric regression model (Fayvishenko et al., 2023). It was concluded that an increase in spending on brand marketing on social networks by 1 billion dollars leads to an increase in the market capitalisation of companies' shares by an average of 1,445,947 U.S. dollars. At the same time, while determining the factors that contribute to the growth of the company's value (brand recognition, increasing the conversion rate, increasing the number of potential customers), the authors do not raise the question of increasing the efficiency of managing the client base to achieve a specific impact on business values. An important issue in the commercial activity of e-commerce enterprises is modelling the lifetime value of the client as a key indicator of commercial activity. Gupta et al. (2006) conducted a classification of models to determine CLV. In the presence of a database of statistical data on the behaviour of regular customers, it is possible to calculate CLV based on actual data and make predictions using mathematical models.

One such model was developed by Schmittlein et al. (1987) called Pareto/NBD, which is a powerful tool for analysing the customer base and has certain disadvantages related to the estimation of its parameters during practical use. To solve this problem, Fader et al. (2005a) proposed an adapted model called BG/NBD, which makes it possible to forecast the number of customer transactions in the future.

It is more convenient and can be implemented practically using Microsoft Excel. However, this model does not consider the variability in the business environment. Harkavenko and Stets (2022) predicted customer behaviour using stochastic Pareto/NBD and Gamma-Gamma models based on the CLV definition. However, the authors correctly pointed out that this model is sensitive to the input data. The distribution of all the input indicators must correlate with the theoretical assumption of the model, which does not always correspond to reality. Therefore, in the case of inconsistencies, the model error increased significantly.

Based on the Pareto/NBD model, some authors have proposed using modified approaches to predict CLV, such as in the retail banking sector (Glady et al., 2009). A new technology for businesses is cognitive analysis (cognitive analytic management, CAM), which is used to manage the client base. A study on this topic confirmed the possibility of using machine learning algorithms to classify customers and determine their lifetime value; however, CLV-based retail customer segmentation methods require improvement (De Marco et al., 2021).

It should be noted that a promising direction for CLV forecasting is the use of neural networks. One such approach forms a multi-output model of a deep neural network with two additional parameters: a clear product category and a trend in the amount spent (Benk et al., 2022). However, this line of research is just beginning and requires neural network training. A review of research on the specified topic indicated the need to adapt modern approaches to modelling marketing strategies, taking into account the unstable conditions of the operating environment of companies in the field of e-commerce.

3. Methodology.

General scientific research methods were used: analysis, synthesis, theoretical generalisation, systematisation, and comparison to highlight the main characteristics of marketing planning tools, methods of grouping information, and choosing the main and additional when formulating the stages of implementation of the GTM strategy.

Special analytical methods are used to forecast the number of client transactions when working with the database. At the initial stage of applying the BG/NBD model, the input set was transformed, and the following indicators were extracted: customer ID, time of the last transaction, number of transactions in a certain period of time, and length of time from which the purchasing behaviour was observed. The data were recorded in the form ($X = x, t_x, T$), where x is the number of transactions during the time (0, T) and t_x ($0< t_x \le T$) is the time of the last transaction (Fader, 2005b).

The resulting dataset contains a sample of 1,207 customers who made purchases through an electronic resource for one year. One week was used as the base unit of time for modelling, and data on purchasing behaviour for 54 weeks were used to build the model; the possibility that a transaction could occur every day of the week was also considered. The main goal was to construct a log-likelihood function during the evaluation of model parameters. At the beginning of the calculations, the expression $\ln[L(r, \alpha, a, b \mid X= x, t_x, T)]$ was used for each of the 1207 customers in the sample; in the Microsoft Excel environment, the values of parameters r, α, a, b were assigned one to start calculations. The log-likelihood function for a randomly selected customer with a purchase history ($X = x, t_x, T$) can be written as (Fader, 2005b):

$$L(r, \alpha, a, b \mid X= x, t_x, T) = A_1 \cdot A_2 \cdot (A_3 + \delta_{x>0} A_4) \quad (1)$$

Where: $A_1 = \Gamma(r+x)\, \alpha^r / \Gamma(r)$;
$A_2 = \Gamma(a+b)\, \Gamma(b+x) / \Gamma(b)\, \Gamma(a+b+x)$;
$A_3 = (1/(\alpha + T))^{r+x}$;
$A_4 = (a/(b+x-1)\, (1/(\alpha + t_x))^{r+x}$;
$\delta_{x>0} = 1$ if $x>0$ and $\delta_{x>0} = 0$ otherwise.

The contribution of an individual client can be written as a log-likelihood function as follows (Fader, 2005b):

$$\ln[L(r, \alpha, a, b \mid X= x, t_x, T)] = \ln(A_1) + \ln(A_2) + \ln(A_3 + \delta_{x>0} A_4) = \ln(A_1) + \ln(A_2) + \ln(\exp(\ln(A_3)) + \delta_{x>0} \exp(\ln(A_4))) \quad (2)$$

Taking into account data on clients, estimates of four parameters of the model are found by maximizing the log-likelihood function. The Microsoft add-on was used to estimate Excel “Solution Search” parameters.

The next step was to build a forecast of repeated purchases in the database (1207 customers). For a randomly selected customer, the formula for calculating the expected number of transactions for a period of time *t* looks like this (Fader, 2005b):

$$E\,(X(t)\mid r, \alpha, a, b) = (a + b - 1)/(a-1)\,[(1 - (\alpha/\alpha + t)^r\ {}_2F_1\,(r, b; a + b - 1; t/(\alpha + t)] \quad (3)$$

where, ${}_2F_1(\cdot)$ is the hypergeometric Gaussian function.

The Gaussian hypergeometric function can be written in the form:

$${}_2F_1\,(a, b; c; z) = \sum_{j=0}^{\infty} \frac{(a)_j (b)_j}{(c)_j} \frac{z^j}{j!},\ c \neq 0, -1, -2, \ldots, \quad (4)$$

where, $(a)_j$ is the Poghammer symbol that denotes the increasing factorial $a(a+1)\cdots(a+j-1)$.

Provided that it is necessary to predict future purchases by a certain customer, information about the previous behaviour of this customer and the parameters of the model are used. The following expression can be used for calculations (Fader, 2005b):

$$E\,(Y(t)\mid X = x, t_x, T, r, \alpha, a, b) = ((a+b+x-1)/(a-1))\ x\,[(1 - ((\alpha+T)/(\alpha+T+t))^{r+x} \cdot {}_2F_1\,(r+x, b+x; a + b + x - 1; t/(\alpha+T+t)]\,/(1 + \delta_{x>0}\,(a/(b + x - 1))\,((\alpha+T)/(\alpha + t_x))^{r+x} \quad (5)$$

The main advantages of the BG/NBD model compared to similar developed models (Pareto/NBD, Gamma-Gamma) are the better availability for programming, and application.

In particular, this model makes it possible to work with actual transaction databases of electronic businesses using built-in Microsoft Excel.

4. Aim and tasks.

This study aims to develop approaches for modelling the marketing strategy of e-commerce enterprises.

This determines the formulation and solution of the following tasks: conducting a comparative characterisation of modern marketing planning tools, an empirical study of the possibilities of using the BG/NBD model for marketing planning in e-commerce companies and taking into account a scenario approach that is appropriate under conditions of risk and uncertainty.

5. Results.

The e-commerce market in Ukraine is characterized by growth trends associated mainly with increased sales in online retail. The chosen policy of investing in the development of digital infrastructure by retail enterprises has a positive effect on online sales volumes.

The decline in retail sales in Ukraine has slowed since the beginning of 2022, but by 2023, it had recovered, and online trade reached the 2021 figures (Table 1). The growth trend in e-commerce volumes may continue in 2024, leading to increased competition in the e-commerce market.

Table 1. Characteristics of the e-commerce market in Ukraine, 2021-2023.

Indicator	Years			Rate of change, %	
	2021	2022	2023	2022/2021	2023/2022
Volumes of retail trade, UAH billion	1 443	1396	1819	- 3,0	+ 30,0
Online sales, UAH billion	129	151	182	+17,0	+ 21,0
Online sales, % of total retail sales	8,9	10,8	10,0	+ 1,3	- 7,4
Number of Internet users, million	25,6	19,0	18,0	-26,0	-5,0
Number of Internet buyers, million	11,0	8,5	9,9	-23,0	+ 17,0

Source: based on PROMODO (2023).

Large-scale transformation processes in all spheres of life encourage businesses to change their behaviour model due to the influence of factors of internal subsystems and the external environment. Despite the weak predictability of such influences, only implementing the concept of strategic planning makes it possible to achieve the set goals. The enterprise's long-term plans are reflected in its primary strategy for development.

However, in the era of marketing 4.0, an effective business strategy for the enterprise can be implemented to create value for customers, employees, and other stakeholders.

Therefore, the marketing strategy as an integral part of the general strategy of the company's development is the key to solving the main task of the formation of value for consumers, as well as rapid changes in technologies, encourage businesses to use new marketing tools and introduce innovations. A marketing strategy is a long-term strategy that defines the overall marketing goals of a business. The mission develops the marketing strategy and conceptually reflects the development of the business, taking into account the company's tasks before the potential customers.

The enterprise's marketing plan reflects a step-by-step plan of actions necessary for conducting a marketing campaign. If the business intends to introduce a new product or service, forming a go-to-market (GTM) for such projects is advisable through communication, marketing and brand strategies. Companies develop a strategy to optimize the risks of introducing a separate product. A typical GTM strategy includes a target risk profile, a marketing plan, and a specific sales and distribution strategy (Coursera, 2024). When promoting products (services) to the market, attention is focused on efficient marketing or tracking customers' online activity based on digital technology data.

Constant external transformations and the emergence of new challenges encourage companies to change internally to use more advanced tools and technologies of marketing strategy, which can be implemented in different ways (Angeloni and Rossi, 2021):

– Digital strategy (plan for the use of digital technologies);
– Communication (channels of communication with the client through which he receives information);
– Brand strategy (the main idea of the company brand),
– PR strategy (building a positive reputation and maintaining effective communication with the target audience);
– Support strategy (in the IT industry – technical support for the client).

Although a GTM strategy may include a marketing plan and be guided by a marketing strategy, neither a marketing plan nor a marketing strategy contains a specific GTM strategy (Kuester et al., 2018). As for the marketing strategy, it is one of the components of the business plan.

Table 2 compares the marketing strategy, marketing plan, business plan and GTM-strategy by individual features.

Table 2. Comparative characteristics of marketing strategy, marketing plan, business plan and GTM strategy.

Marketing strategy	**Marketing plan**
Content and focus:	
A comprehensive plan of marketing actions. A component of the business plan.	A roadmap supporting the marketing strategy according to which the company will implement its marketing activities.
Purpose, functional purpose:	
Create a brand, attract customers, and stimulate them for long-term cooperation. Helps maximize return on investment by maintaining marketing focus and measuring sales performance.	Provide information about the marketing campaign at a tactical level, namely: what is planned to be done, where it will take place, when it will be implemented and how the results of the marketing plan will be tracked.
Planning period:	
Long-term, endless, often repeated.	Long-term and short-term.
Business plan	**GTM strategy**
Content and focus:	
Defining business goals and how the company will achieve them.	A component of a marketing strategy that is focused on marketing a single product or service.
Purpose:	
A framework for seeking growth by monetising the creation of customer value, aimed at finding investors.	Bring the product to the market.
Planning period:	
Long, endless, rarely repeated.	Short-term, ending after product launch.

Source: based on Coursera (2024), Makosiewicz (2021).

Having a GTM strategy contributes to the company's competitive advantages in the market if it is adapted to the needs of its customers. With the help of GTM strategy, it is possible to define the ideal client and to form and provide him with the necessary information. The main task of a company that offers its product to the market is to convey its value to the client. If this task is performed successfully, the company can optimize sales tactics and capture a significant market share despite competition, economic uncertainty and risks.

Developing an effective GTM strategy should include market and marketing cost analysis, taking into account the following stages of GTM strategy implementation:

1. The study of the target market, competitors, customer needs and current market trends is based on data collection to determine the ideal customer for the product or service being marketed (INSEED, 2022).
2. Selection of target markets and choosing a specific group of consumers taking into account the needs, preferences and their behaviour in order to adapt the marketing strategy to meet their needs.
3. Building a marketing sales funnel to form a company communication channel with representatives of the target audience.
4. Planning the launch of a product or service on the market based on cross-functional communication between sales and marketing departments.
5. Implementation of the GTM strategy. A clear visualization of the marketing strategy should be complemented by such principles of its implementation as flexibility and adaptability to changing operating conditions.

Whatever marketing planning tools are used in business activities, e-commerce is customer-oriented. Hence, the formation and management of the customer base is one of the main tasks of marketing.

In modern business activities, enterprises accumulate data stored in their client base. Marketing effectiveness can be assessed based on the following metrics (INSEED, 2022):

- Customer acquisition costs (CAC);
- Customer lifetime value (CLV);
- Conversion rate;
- Social media engagement.

About 76% of companies consider customer lifetime value the most essential marketing metric (Saleh, 2015).

Qualitative forecasting and use of marketing metrics, in particular, the customer lifetime value indicator (other designations of this metric are "customer lifetime value" or "customer lifetime revenue"), reflect the average revenue that a company receives from a customer during a certain period (Reminny, 2023).

The analysis of stochastic models of customer base management and their modifications showed that the BG/NBD model has certain advantages over existing developments, provides an opportunity to identify active and inactive customers and predict future transactions based on transactions made in the past (Fader, 2005b).

The BG/NBD model allows companies to segment customers by activity and assess customer life cycle value. The use of the model contributes to more effective planning of marketing strategies and management of costs for attracting and serving customers, which, as a result, has a positive effect on business profitability.

Practical use of the model BG/NBD, based on the existing set of data on customer behaviour, provides for the following actions:

1. Estimation of model parameters.
2. An aggregated sales forecast is generated based on the estimated parameters in the first step.
3. Forecasting future purchases of a specific customer using information about past behaviour and estimated model parameters.

The input data set (UC Irvine Machine Learning Repository, 2019) contains statistics about customer transactions in e-commerce with the following fields: account number, product code, product description, product quantity, transaction date, price per product unit, customer ID, and customer country of origin. The four parameters of the BG/NBD model (r, α, a, b) were estimated by maximizing the log-likelihood function according to formulas 1 and 2.

The "Solution Search" add-in was used in Microsoft Excel to estimate the parameters.

With the help of this tool, the objective function is maximized, the value of the log-likelihood functions and also the restriction is used, namely: the parameters *r, α, a*, and *b* are set to values greater than 0 (more precisely, these values must be greater than a small positive value of 0.00001 (one hundred thousandths). Several calculations were carried out using the specified Microsoft Excel tool. The maximum value of the log-likelihood function was obtained, equal to 14460.54 and the following parameter values: r = 0.1101, α =0.00001, a=170.37, b=16458.73.

After obtaining the results of the evaluation of the model parameters, the features of building a forecast of repeat purchases in the database (1207 customers) were considered. The expected values of repeat transactions were calculated for each customer using formulas 3 and 4 in a Microsoft Excel. When predicting future purchases by a specific customer, information about the previous behavior of this customer and model parameters is used with formula 5.

A calculation was performed on a customer randomly selected from the above database (customer ID = 15461) with the following inputs: x = 5, t_x = 30.43, T = 53.29 and calculated the expected number of transactions for weeks 55–80 (i.e., t = 26). When using equation (3), one should pay attention to the Gaussian hypergeometric function, estimated by the abovementioned method. After the calculations, information was obtained that the selected client would make 2.35 transactions during 55–80 weeks (Fig. 1).

	A	B	C	D	E	F	G
1	r	0,110		2F1	7,427904672		
2	alpha	0,000		a	5,110		
3	a	170,367		b	16463,725		
4	b	16458,725		c	16633,092		
5	History of customer behavior			z	0,327910162		
6	x	5		Terms			
7	t_x	39,72		0	1		
8	T	53,29		1	1,658591176		
9	t (forecast period, weeks)	**26**		2	1,644628823		
10				3	1,26512328		
11		**E (Y(t)|X=x,t_x,T)**	2,35	4	0,832549054		
12				5	0,492350075		
13				6	0,269270958		
14				7	0,138714232		
15				8	0,068153884		
16				9	0,032223018		
17				10	0,014757361		
18				11	0,006579547		
19				12	0,002866988		
20				13	0,001224752		

Fig. 1. Results of forecasting the number of client transactions.

The parameters of the model for forecasting, the history of the client's behaviour and the forecast of his transactions for the next 26 weeks are shown in the Table 3.

Table 3. Model parameters and predictor of the number of customer transactions.

Model parameters		**Core**
r	0.110	
alpha	0.0000100	
a	170.367	
b	16458.725	
History of customer behaviour		
x	5	
t_x	39.72	
T	53.29	
t (forecast period, weeks)	**26**	
Predictive indicator of the number of customer transactions	**E (Y(t) | X=x, t_x, T)**	**2.35**

Based on the purchase history of other customers, it is possible to carry out similar calculations ($X = x$, t_x, T) and the forecast horizon (t), resulting in a forecast of future transaction values for each customer.

Therefore, the use of the BG/NBD model, a customer behaviour model, in the presence of the purchase history of e-business customers makes it possible to predict the behaviour of customers and the indicators of future transactions that they will make. The main data are model parameters, which are calculated using a properly prepared sample with client data.

The management of the customer base significantly affects the efficiency of the enterprises, so, according to the Bain & Company consultant, a 5% increase in the level of customer retention can lead to an increase in profit from 25% to 95% (Reichheld, 2001).

Monitoring forecasting results helps to solve the problem of creating value for consumers. It allows finding new marketing tools for forming a pool of regular customers, which in the long run can contribute to reducing business costs, acting as promoters and bringing new customers.

In the new realities, even traditional companies are forced to conquer the digital space, promoting their products to the market in conditions of uncertainty and risks. Instability has become an integral attribute of every part of the world, and the challenges are becoming increasingly complex: wars, migration, natural disasters, outsourcing of labour, and changing needs and aspirations of people. All this must be considered when planning commercial activities to avoid undesirable or even catastrophic consequences.

The indicator of the customer's lifetime value provides a critical understanding of the company's marketing behaviour and the perspective of its development. CLV forecasting is traditionally based on transaction data already generated in the company's customer base, assuming that the data reflects the immutability and consistency of each customer's actions. However, the business landscape often undergoes unpredictable changes, which also have consequences for the CLV indicator.

Businesses should focus on developing various scenarios, three of which are traditional: basic, optimistic and pessimistic.

The BG/NBD model can be used as a scenario approach when predicting repeat customer purchases. Integrating the BG/NBD model and the scenario approach is possible if the e-business company enters a known market with existing competitors. For such forecasting, it is necessary to follow the sequence of actions:

1. Data on competitors' sales in a certain market segment is collected.
2. Prepare the data in a format that can be used in the model.
3. Search for model parameters. Formation of three sets of model parameters according to possible scenarios.
4. Using model parameters to predict customer behaviour for each scenario.

The retained values of forecast transactions by clients are used in the scenario approach to modelling the CLV indicator, which involves the creation of several possible scenarios of the development of events that can affect clients' behaviour. The algorithm of the general scenario approach is shown in Fig. 2.

According to the algorithm displayed in Fig. 2, the BG/NBD model is an integral part of the scenario approach for predicting customer lifetime value since the forecast of purchase frequency is the most important indicator for calculating CLV.

One of the methods is reflected in the article by Fader et al. (2005b) and makes it possible to calculate this indicator according to the formula:

$$CLV = m*r/(1 + d - r) \quad (6)$$

where m is the average net cash flow from the client for a certain period, r is the client retention rate, d is the rate discounting.

As one of the options for the value of m, the gross profit from the client can be used, which is calculated according to the formula: m = gross profit rate (%) x average revenue from the client during its life cycle.

The customer retention rate "r" is the percentage of customers who made a repeat purchase in a certain period of time, compared to the previous period, and is calculated using the ratio:

$$r = (C_e - C_n)/C_b*100\% \quad (7)$$

where, C_e is the number of customers at the end of the period, C_n is the number of new customers that appeared during the period; C_b is the number of customers at the beginning of the period.

It should be noted that at the second stage of using the scenario approach (part 2), it is necessary to collect additional information about customers: average customer check, customer retention rate, and customer acquisition costs (CAC).

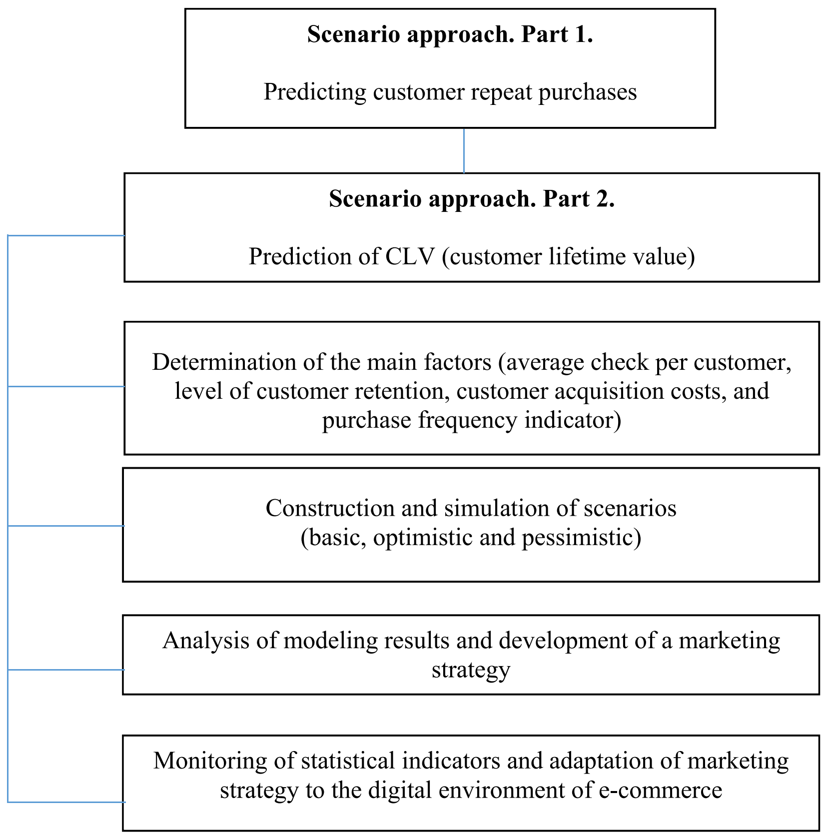

Fig. 2. Algorithm of the scenario approach for CLV modelling.

The third stage is to construct and model customer behaviour scenarios to use the results obtained while further developing the company's marketing strategy. Building scenarios, analysing simulation results, developing a marketing strategy, monitoring statistical indicators, and updating the marketing strategy are cyclical. It must be constantly improved during the practical implementation of the project.

Thus, the scenario approach enables e-commerce enterprises to implement variable marketing planning, reducing risks in conditions of growing uncertainty. A well-designed marketing strategy that can be adapted to different scenarios of business development allows you to increase the sales of an e-commerce company.

6. Conclusions.

The study of theoretical and practical aspects of e-commerce showed a significant influence of marketing planning on developing this area of the digital economy. Marketing planning can be implemented by developing a marketing strategy, which can be reflected in a marketing plan, GTM strategy, or project business plan.

A comparative characterization of various marketing planning tools was carried out according to such features as content and focus, purpose, functional purpose, and planning period. The expediency of building an effective GTM strategy for successfully launching a new product for an e-commerce company is substantiated.

The logical sequence of the formation of the GTM strategy was established: research of the market and the target audience; selection of target markets and segments; building a marketing sales funnel; planning the launch of a product or service on the market; implementation of the GTM strategy.

Based on the analysis of literary sources, it was determined that NBD modelling is an effective tool for segmenting customers by activity and estimating the cost of the customer's life cycle. An empirical study of the possibilities of using the BG/NBD model for marketing planning in e-commerce companies showed that for the simulation of indicators that affect the company's marketing strategy, it is important at the initial stage to convert the database of customer purchases into the input format required for modelling. CLV maximization is a criterion for optimal management of the client base and contributes to the achievement of the company's business goals.

However, the customer base data set usually does not meet the required format and needs to be converted. To automatically obtain the required data format, a Visual Basic program was developed. A forecast of customer behaviour was built, and the customer transaction indicator was determined for further CLV calculation.

In order to reduce risks in conditions of uncertainty, it is proposed to apply the BG/NBD model within the framework of a variable approach, which provides for the creation of several possible scenarios of the development of events that affect the behaviour of customers in different ways. According to the recommended algorithm, the BG/NBD model acts as a component of the scenario approach for forecasting the cost of the customer's life cycle, which in turn allows more flexible forecasting of digital business revenues and building an optimal marketing strategy.

REFERENCES

Angeloni, S., & Rossi, C. (2021). An analytical model for comparing the profitability of competing online marketing channels: Search engine marketing versus e-commerce marketplace. The Journal of Marketing Theory and Practice, 29(4), 534–549. https://doi.org/10.1080/10696679.2021.1879656

Bazaluk, O., Kader, S. A., Zayed, N. M., Chowdhury, R., Islam, M. Z., Nitsenko, V. S., & Bratus, H. (2024). Determinant on economic growth in developing country: A special case regarding Turkey and Bangladesh. Journal of the Knowledge Economy. https://doi.org/10.1007/s13132-024-01989-8

Benk, G. Y., Badur, B., & Mardikyan, S. (2022). A New 360 Framework to Predict Customer Lifetime Value for Multi-Category E-Commerce Companies Using a Multi-Output Deep Neural Network and Explainable Artificial Intelligence. Information, 13(8), 373. https://doi.org/10.3390/info13080373

Coursera. (2024). What Is a Go-To-Market Strategy? And How to Create One. https://www.coursera.org/articles/go-to-market-strategy

De Marco, M., Fantozzi, P., Fornaro, C., Laura, L., & Miloso, A. (2021). Cognitive analytics management of the customer lifetime value: an artificial neural network approach. Journal of Enterprise Information Management, 34(2), 679–696. https://doi.org/10.1108/jeim-01-2020-0029

ECDB. (2024a) eCommerce market in Ukraine. https://ecommercedb.com/markets/ua/all

ECDB. (2024b). Global eCommerce Market 2024. http://surl.li/ipmmhb

Fader, P. S., Hardie, B. G. S., & Lee, K. L. (2005a). “counting your customers” the easy way: An alternative to the Pareto/NBD model. Marketing Science, 24(2), 275–284. https://doi.org/10.1287/mksc.1040.0098

Fader, Peter S., Hardie, Bruce G. S., & Lee, Ka Lok. (2005b). Implementing the BG/NBD Model for Customer Base Analysis in Excel, 8. https://brucehardie.com/notes/004/bgnbd_spreadsheet_note.pdf

Fayvishenko, D., Cherniavska, L., Bondarenko, I., Sashchuk, T., Sypchenko, I., & Lebid, N. (2023). The impact of brand social media marketing on the dynamics of the company's share value. Business: Theory and Practice, 24(1), 24–32. https://doi.org/10.3846/btp.2023.17117

Glady, N., Baesens, B., & Croux, C. (2009). A modified Pareto/NBD approach for predicting customer lifetime value. Expert Systems with Applications, 36(2), 2062–2071. https://doi.org/10.1016/j.eswa.2007.12.049

Gupta, S., Hanssens, D., Hardie, B., Kahn, W., Kumar, V., Lin, N., Ravishanker, N., & Sriram, S. (2006). Modeling customer lifetime value. Journal of Service Research, 9(2), 139–155. https://doi.org/10.1177/1094670506293810

Harkavenko, V., & Stets, O. (2022). Economic and mathematical model of enterprise client base management. Strategy of Economic Development of Ukraine, 50, 177–196. https://doi.org/10.33111/sedu.2022.50.177.196

INSEED. (2022). 10 steps to creating a successful go-to-market strategy GTM. http://surl.li/pzfycc

Kotler, P., Katarjaya, H., & Setiavan, Y. (2021). Marketing 4.0: Moving from Traditional to Digital. KM-Buks.

Kuester, S., Konya-Baumbach, E., & Schuhmacher, M. C. (2018). Get the show on the road: Go-to-market strategies for e-innovations of start-ups. Journal of Business Research, 83, 65–81. https://doi.org/10.1016/j.jbusres.2017.09.037

Makosiewicz, M. (2021). How to build a go-to-market strategy in 8 steps. SEO Blog by Ahrefs. https://ahrefs.com/blog/building-a-go-to-market-strategy

Morokhova, V., Batyrbekova, Z., Bondarenko, O., Ustik, T., Saiensus, M., & Travin, V. (2023). Digitalization strategies for marketing communications to build relationship marketing: Modern solutions in brand management. WSEAS Transactions on Environment and Development, 19, 1231–1245. https://doi.org/10.37394/232015.2023.19.112

PROMODO. (2023). Like Ukrainian eCommerce survived 2023. https://www.promodo.ua/yak-ukrayinskiy-ecommerce-pereziv-2023

Reichheld, F. (2001). Prescription for cutting costs. https://media.bain.com

Reminny, S. (2023). Startup kitchen. The IT business book I've been missing. Kyiv. Nash Format.

Saleh, K. (2015). Customer Acquisition Vs.Retention costs – statistics and trends. Invesp - Conversion Rate Optimization Blog. https://www.invespcro.com/blog/customer-acquisition-retention

Schmittlein, D.C., Morrison, D.G., & Colombo, R. (1987). Counting your customers: Who are they and what will they do next? Management Science, 33 (1), 1–24.

UC Irvine Machine Learning Repository. (2019). Online Retail. http://archive.ics.uci.edu/dataset/502/online+retail+ii

Ukrainian Institute of the Future. (2024). Ukraine 2030E – a country with a developed digital economy. https://strategy.uifuture.org/kraina-z-rozvinutoyu-cifrovoyu-ekonomikoyu.html