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The Impact of Selected Variables on Customer Lifetime Value

Daniel Kvíčala[1], Halina Starzyczná[2], Ondřej Mikšík[3]

[1]*Silesian University, School of Business Administration, Univerzitní nám. 1934/3, 733 40 Karviná*
Email: kvicala@opf.slu.cz

[2]*Silesian University, School of Business Administration, Univerzitní nám. 1934/3, 733 40 Karviná*
Email: starzyczna@opf.slu.cz

[3]*Silesian University, School of Business Administration, Univerzitní nám. 1934/3, 733 40 Karviná*
Email: miksik@opf.slu.cz

Abstract: The current political and economic environment is exerting significant pressure on both the broader economy and overall living standards. A decline in demand is evident in the online environment, negatively affecting the financial results of e-commerce platforms. This situation requires increased efficiency across all business activities, particularly marketing, for economic growth, maintaining market positions, or even survival. For these purposes, it is essential to provide new insights to support strategic decisions generated through data analysis using an appropriate methodology. Empirical data from several e-commerce platforms were utilized and analysed using Vector Autoregression (VAR). The results indicated that the only variable with a clear impact on the development of CLV is the number of visits that a customer makes to the respective e-commerce platform, a finding consistent across all cases examined. These findings provide valuable insights for both academic research and managerial practice to estimate e-commerce performance and make informed marketing decisions. Therefore, the conducted research provides valuable information on the factors that influence customer lifetime value in the context of e-commerce. However, certain limitations must be acknowledged that affect the generalisability and precision of the findings. These limitations include the number of platforms examined and their customer bases, the set of metrics investigated, the study timeframe, and alternative mathematical and statistical methods for a more comprehensive comparison of results. Recognising these limitations paves the way for future research that will address these aspects, refine and expand our understanding of customer behaviour and value creation in the digital marketplace.

Keywords: customer value, e-shop, metrics for monitoring customer behaviour, Vector Autoregression (VAR).

JEL classification: L81, M31

Introduction

The dynamic growth of electronic commerce requires the acquisition of insights from this environment to understand and create effective marketing strategies. In the e-commerce landscape, specific marketing channels are employed, enabling extensive data collection for further analysis. These channels play a key role in shaping customer interactions and behaviour, generating a wealth of information that can be harnessed for strategic decision making.

Customer lifetime value (CLV) proves to be a valuable metric in this context, offering a means to assess the performance of marketing channels and determine the value of individual customers (Yoo et al. 2020). The aggregation of CLV across all customers further provides a holistic expression of the company's value (Ali, N. & Shabn, O. S. 2024). Using data analytics, it becomes possible not only to evaluate CLV but also to predict it, offering a predictive dimension to the assessment of a company's value.

Despite the extensive availability of data and the maturity of the e-commerce sector, there remains a notable scarcity of empirical scientific studies (Platzer & Reutterer 2016, Chamberlain et al. 2017). This article addresses this gap, positioning itself as an original and potentially invaluable source of new insights applicable in both academic and business contexts. By exploring the untapped potential of e-commerce data, the article contributes to the growing body of knowledge and opens avenues for further research, making it a valuable resource for academic and practical purposes.

The purpose of the article is to identify the determinants of the Customer Lifetime Value (CLV) through an analysis of the relationship between selected variables and CLV. The variables under consideration describe customer behaviour on the website, specifically, the number of website visits (V), the number of ad impressions through selected online marketing channels (I), the average duration of a customer's website visit (ASD), the average number of pages visited (PPS), and the cost per thousand ad impressions on online marketing channels (CPM). The results of the analysis will have implications both for academics and practitioners.

As the data are sourced from Google Analytics, a globally used tool, and the metrics applied are commonly used across the e-commerce environment, the insights gained can be broadly applicable to almost any e-commerce platform, albeit with consideration for the research limitations. The research focuses on six Czech e-commerce platforms offering diverse product ranges. The subject of the study is customer behaviour and selected metrics that describe the performance of online marketing channels. Research questions and hypotheses were formulated, and the Vector Autoregression (VAR) method was applied to verify the variables and their impact on CLV.

1 Theoretical background

The starting point will be the Customer Lifetime Value (CLV) and customer behaviour using digital metrics to examine customer buying behaviour, the performance of online marketing channels, and their impact on CLV.

The goal of these measurements is to provide reliable information on customer behaviour, actions, and sales revenue (Laudon & Traver 2021). There are various metrics, each with its specific use, meaning that each may be suitable for different situations. In practice, this implies the need to apply combinations of metrics to monitor customer behaviour.

Metrics can be divided into three groups: customer-related metrics, e-commerce performance, and campaign metrics. Customers visit websites with the intention of making purchases and performing various activities on them. Many experts are interested in a list of metrics that have informative value (Ghandour et al. 2011, Hojdik 2017). The website plays a crucial role and should be functional, engaging, and capable of facilitating conversions and customer retention, as well as evoking their activities with other members of their target group. Therefore, metrics such as the number of visits to the website (V), the average page views per visit (PPS), and the average time a customer spends on the website (ASD) are monitored.

To express the value of customers for an e-shop and subsequently identify the most profitable customers, Customer Lifetime Value (CLV) is commonly used. CLV is generally defined as the sum of revenues obtained from a particular customer during the measurement period, reduced by the sum of costs associated with selling products (Kumar & Reinartz 2016). Additionally, the CLV serves as a good indicator of the overall value of the company in terms of current and future customers (Norouzi 2024).

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One way to collect the necessary customer data is by using the Google Analytics platform, widely used globally. This platform gathers information about customer behaviour on the website, sales performance, page visits, specific product interactions, and more. All data can be analysed using pre-set dashboards, which can be customised according to specific needs. Additionally, the data can be exported for processing in other tools.

The interrelationship between these and other metrics, their impact on selected performance indicators, and the prediction of future trends have been the focus of research by various authors. For example, Gunter and Onder (2016) analysed data obtained from Google Analytics, similar to the data used in this article. Using an analysis of selected metrics, these authors could predict the number of visitors to Vienna during a specific time period, demonstrating the utility of such data not only in the online but also in the offline environment. Another study by Golovko and Schuman (2019) explored employee recruitment and stimulation through Facebook communication. The authors found a positive relationship, indicating that the posting of HR-focused content helped increase the number of applicants for specific positions. Roy and Sharma (2021) examined the interrelationships between ASD, BR, and RV and their relationship with website conversion completion and conversion rates. However, this study focused on a website where customers met a specific goal rather than making a purchase. The results showed that ASD and RV had an impact on achieving the goal, with a negative relationship identified for BR. A commonality among these studies is that they all worked with data from a single company, despite differences in origin and size. Another shared characteristic is the methodology used, as all authors employed the VAR method. This method is suitable and widely used for the analysis and prediction of time series in various fields (Golovko & Schumann 2019; Faehnle & Guidolin 2021, a b).

2 Research methodology

As mentioned earlier, the e-commerce environment provides an overwhelming amount of data about customer behaviour and activities related to purchasing. These activities include website visits, their frequency or duration, the number of pages visited in general or specific pages, and the source of the visit, i.e., the channel through which the customer came to the website (search engine, social media, email, etc.). Companies can leverage all this information for analysis and subsequently make strategic or tactical marketing decisions. Additionally, data on communication activities by companies are available, such as the communication channels used, the number of visitors or customers acquired through these channels, and the associated costs. Companies can also track data on the effectiveness of websites or e-shops, as well as current product trends expressed by the volume of searches for a particular product category. This list of data possibilities in the e-commerce domain is by no means exhaustive. However, for the purposes of this article, the focus will primarily be on customer behaviour, the performance of e-shops, and the online marketing activities of companies. Online marketing activities include campaigns conducted on platforms such as Meta, Google, or Sklik.

The research aims to identify variables that help explain the development of customer lifetime value (CLV). In this study, customer activity metrics and website performance metrics are examined as endogenous variables. The term "endogenous variables" indicates that each variable (metric) is influenced by its own history (lagged data) and the historical values of other variables (Roy & Sharma 2021). For this purpose, the Vector Autoregression (VAR) method will be used, which analyses the relationship between variables with a certain time delay (Faehnle & Guidolin 2021). This property enables a more nuanced understanding of how e-shop activities manifest in customer purchasing behaviour and, ultimately, how they influence e-shop performance expressed by profit. Other reasons for using this method in the context of the article's goal have been cited by, among others, Golovko and Schumann (2019) and Roy and Sharma (2021):

Firstly, the VAR approach takes into account the dynamic interaction between website performance results and consumer activity on this website. This model can capture the online shopping behaviour of consumers in real time through multiple interactions with the website before making a final purchase.

Second, the VAR model allows measuring the overall impact of one variable, assuming that past effects of other variables are also considered.

Third, successful online transactions (both financial and non-financial) on the website can motivate customers to make repeated visits and purchases on the same website. In this way, the resulting variables can influence the future activities of customers on the website.

Data

The research used data from six Czech e-shops that span various product categories over a period of 31 months. The data, sourced from Google Analytics, are categorised on a daily basis and encompass more than 216 thousand transactions, 400 million CZK in revenue, and 41 million CZK in costs associated with selected metrics assigned to online activities. Table 1 provides an overview of the basic numerical indicators for each individual e-shop.

Table 1: E-shops characteristics

Products	E-shop number	Transactions	Revenues CZK	Costs CZK
Alcohol	1	1 944	2 573 886	532 655
Gifts	2	19 419	28 720 734	4 588 508
Pets	3	23 784	27 015 284	2 696 297
Fitness	4	20 490	20 327 594	2 248 288
Hobby	5	52 950	143 842 248	7 541 410
Sport clothing	6	97 872	178 633 156	23 354 190
Overall		216 459	401 112 902	40 961 348

Source: own

For the analysis, metrics describing customer behaviour were selected, aligning with studies mentioned in the theoretical part (Gunter and Onder 2016, Roy and Sharma 2021), along with metrics characterising the performance of the e-shop and on-line marketing activities. In total, six variables were chosen, as shown in Table 2, which will be subject to further analysis.

Table 2: Description of the chosen variables

Dimension	Metrics	Shortcut
Customers	Number of visits of the e-shop by customer	V
	Average number of pages visited by the customer	PPS
	Average duration of the customer’s session	ASD
Marketing channels	Number of ad impressions	I
	Cost per 1,000 ad impressions	CPM
Value	Customer lifetime value	CLV

Source: own

Subsequently, the selected variables will be incorporated into the VAR model.

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Application of the VAR Method and hypotheses

First, the endogenous variable, which aligns with the article's goal of customer lifetime value (CLV), will be defined. Other variables will be considered exogenous (independent variables). As indicated in Table 2, it involves the number of visits, the average number of pages viewed per visit, the average time spent on the website, the number of impressions of advertisements, and the cost per thousand impressions of advertisements.

Subsequently, a stationarity analysis will be conducted to clarify whether the selected variables are suitable for the chosen method. For each e-shop, the lag length (in days) at which the selected exogenous variables affect the CLV will be determined. The lag length will be determined on the basis of the Schwarz information criterion (SC). This criterion was chosen based on the literature and was found to be the most informative for various dataset sizes, period lengths, and divisions into months, years, or quarters (Ivanov and Kilian 2005). Diagnostic tests of the selected VAR model will follow to verify whether the roots of the estimated autoregressive polynomial lie inside the unit circle in the complex plane, confirming the stationarity of the model.

Finally, Granger causality will be employed to identify the variables that help explain the development of profit value for each e-shop. We can formulate the following null hypotheses:

1. **H01:** The number of ad impressions (I) does not contribute to explaining the development of the customer lifetime value (CLV).

2. **H02:** The number of visits to the website by the customer (V) does not contribute to explaining the development of the customer lifetime value (CLV).

3. **H03:** The average time spent on the website by the customer (ASD) does not contribute to explaining the development of the customer lifetime value (CLV).

4. **H04:** The average number of pages visited by the customer in one visit (PPS) does not contribute to explaining the development of the customer lifetime value (CLV).

5. **H05:** The cost per 1000 ad impressions (CPM) does not contribute to explaining the development of the customer lifetime value (CLV).

3 Results and discussion

Now, the individual steps of the VAR method will be implemented and the results will be presented later.

3.1 Results

The lag length of the influence of variables on the CLV value and stationarity

The first assumption of the method used has been met, as all variables for all e-shops are stationary, and we can proceed with further analysis. The lag length varies across e-shops, ranging from one (e-shops 1 and 6) to two days (e-shops 2, 3, 4, and 5), as shown in Table 3. For e-shops 2 and 3, the lag length was determined using both the SC criterion and the HQ criterion.

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Table 3: The lag time of individual e-shops

E-shop	Numbers	Lag (days)
Alcohol	1	1
Gifts	2	2
Pets	3	2
Fitness	4	2
Hobby	5	2
Sport clothing	6	1

Source: own

The diagnostic of selected models confirmed the stationarity condition, since the values of the roots of the estimated autoregressive polynomial lie inside the unit circle in the complex plane in all examined cases.

Granger causality

Through Granger causality, variables explaining the development of CLV were identified. A summary of the results is available in Table 4.

Table 4: Influence of chosen variables on CLV

Numbers	Product	Number of impressions of ads (I)	Number of visits (V)	Average session duration (ASD)	Average number of pages visited per session (APS)	Cost per 1000 ad impressions (CPM)
1	Alcohol	FALSE	TRUE	FALSE	FALSE	TRUE
2	Gifts	TRUE	TRUE	FALSE	FALSE	FALSE
3	Pets	TRUE	TRUE	TRUE	FALSE	TRUE
4	Fitness	TRUE	TRUE	TRUE	TRUE	TRUE
5	Hobby	TRUE	TRUE	TRUE	TRUE	FALSE
6	Sport clothing	TRUE	TRUE	FALSE	TRUE	TRUE

Source: own

For all e-shops, it was found that V (number of visits) helps to explain the value of CLV. Except for e-shop 1, this also applies to the value of I (number of ad impressions). In three cases (3, 4, 5), the influence of ASD (average time - the time a customer spends on the website) and PPS (average number of pages viewed per visit) was demonstrated for e-shops 1, 2, and 3. CPM (cost per 1000 ad impressions) helps explain the value of CLV for e-shops 1, 3, 4, and 6.

The null hypothesis can be completely rejected only in the case of H02, where the influence of the number of visits to the website by the customer was found to be a factor affecting CLV for all e-shops. For the other metrics, positive impact on CLV was not proven for one or more e-shops.

Discussion

In the examination of various e-commerce platforms, the number of website visits consistently contributes to explaining CLV. Across all scrutinised online retail entities, the frequency with which a customer visits the website emerges as a key determinant influencing the CLV. This finding highlights the importance of customer engagement through online interactions in shaping the long-term value derived from each customer relationship. The positive correlation between website visitation frequency and CLV highlights the pivotal role of sustained and meaningful online engagement in fostering customer loyalty, thus contributing substantially to the overall profitability of e-commerce enterprises. The results are in line with Roy and Sharma (2021) and Xiaozhou (2019), these authors have also demonstrated a positive impact of ASD. However, in our case, this influence was not universally confirmed across all the examined e-commerce platforms. The positive effects of V were confirmed by Chamberlain et al. (2017), Venkatesan and Kumar (2004), as well as Ortiz-Cordova and Jansen (2012).

Five out of six e-commerce companies exhibited a positive correlation between the number of ad impressions and the customer lifetime value (CLV). This aligns with the supporting evidence from Kireyev et al. (2016), Paulson et al. (2018), and Papadogiannakis et al. (2023). The positive impact of ad impressions on CLV suggests that effective advertising exposure can contribute significantly to the long-term value derived from customer relationships in the context of online retail.

For four e-commerce platforms, it was observed that CPM (Cost Per Mille) contributed to the development of Customer Lifetime Value (CLV). This positive relationship aligns with findings supported by research by Saura et al. (2022), Jun and Lee (2010), and Ortiz-Cordova and Jansen (2012). The association between CPM and CLV highlights the significance of advertising efficiency, as reflected in the cost per thousand impressions, in influencing the long-term value derived from customer relationships within the e-commerce domain.

In half of the examined cases, it was observed that the average time spent on the website plays a significant role in explaining the trajectory of Customer Lifetime Value (CLV). This aligns with findings from studies conducted by Kantanantha and Awichanirost (2022). The documented influence of customer dwell time on CLV underscores the importance of the duration customers spend on a website in shaping the long-term value derived from their interactions. This observation suggests that improving the online user experience, optimising website content, and prolonging customer engagement can contribute positively to the overall profitability of e-commerce platforms.

In half of the cases examined, a positive relationship was also observed and was also observed between the number of pages visited and the Customer Lifetime Value (CLV), affirming findings of studies Sulova (2019) and Medeiros and Vidor (2018). However, it is noteworthy that Vaughan (2004) contradicts the influence of this variable on the development of CLV.

This discrepancy highlights the nuanced nature of the relationship between the number of visited pages and the CLV, suggesting that the impact of this variable may be dependent on various contextual factors.

Other factors that were not included in the study but, according to existing research, may have an impact include loyalty, respectively, the number of repeat purchases (Jasek et al. 2019, Segarra-Moliner & Moliner-Tena 2022, Amendah et al. 2023). Service quality and customer satisfaction, identified as primary areas of focus for companies, as indicated by various studies (Cambra-Fierro et al. 2018, Gao et al. 2020, Dandis et al. 2022, Karaboga 2023), were not included in the current research. Therefore, it is not possible to confirm or refute its positive impact on customer value, as it was not part of the study. These factors, as highlighted by the existing literature, remain crucial considerations for businesses, emphasising the need to address service quality and customer satisfaction to enhance the overall value of the customer.

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Conclusion

The fact that the number of visits (V) and the volume of impressions from advertisements (I) contribute to explaining the development of the Customer Lifetime Value (CLV) across all examined subjects (for I, in 5 out of 6 cases) suggests that these two metrics can be used to predict the future trajectory of CLV. Beyond prediction, these metrics, or the activities that lead to changes in these variables, can be used to target CLV stimulation. These results suggest that by increasing the number of website visits or the volume of ad impressions, a company may potentially enhance the CLV of its customers. However, an increase in both values may also have a secondary impact, that is, increasing brand or product awareness. Increasing advertising exposure to a broader audience or directing more people to the website, where products, benefits, or competitive advantages can be showcased, can also boost brand awareness and, consequently, the likelihood that these individuals will make future purchases.

Apart from the immediate impact (considering the delay in impact, as analysed), we can also consider the influence that manifests over a longer timeframe. The stimulation of these variable values can be used not only for prediction, but also for targeted CLV stimulation. These results suggest that by increasing the number of website visits or the volume of ad impressions, a company may potentially improve the CLV of its customers. Increasing both values can also have a secondary impact, namely, increasing brand or product awareness. The results suggest that if a company advertises to a larger audience or directs more people to its website, where it can present its products, benefits, or competitive advantages, it can also enhance brand awareness and, consequently, the probability that these people will make purchases from the company in the future.

Increasing these variables is relatively straightforward for an e-commerce platform. The solution lies in using online marketing channels to distribute relevant content to specific people or customer segments. For these purposes, e-commerce platforms can employ a wide range of tools such as Google Ads, Sklik, Facebook, Instagram, TikTok, price comparison websites, or other channels. These tools allow for targeting based on various criteria, including demographic, geographic, or behavioural characteristics of customers, or re-engaging individuals who have previously made purchases or visited the e-commerce platform, a strategy known as remarketing.

The cost per 1000 ad impressions (CPM) influenced CLV development on 4 out of 6 e-commerce platforms. These platforms should consistently monitor their value and subsequently carry out appropriate marketing activities based on the acquired information. Although increased advertising prices generate higher costs, they ultimately contribute to increased CLV, which is crucial for an e-commerce platform.

As for the metrics ASD and PPS, which contributed to explaining CLV in 3 cases, but for different e-commerce platforms, they may be considered as the least significant. The fact that a person spends more time on a website or visits more pages does not necessarily mean that this person will make a purchase and thus contribute to increasing CLV. However, it is important for these e-commerce platforms to monitor these metrics, as they can provide insights into visitor satisfaction with the website and overall assessment of the website from a customer behaviour perspective. Very low values of these variables, combined with the absence of purchases, may indicate that customers did not find the desired content or are not willing to spend any time on the website. Reasons could include low quality information, design, user-friendliness, or insufficient trust.

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As mentioned in the theoretical part (Mikulášková & Sedlák 2015), well-crafted advertising can have a positive impact on customer engagement. This is closely related to the appearance of the website, where functionality, attractiveness, and graphical design positively influence the generated revenue and profits of companies.

Marketing 4.0 (Kotler, Kartajaya & Setiawan 2016) is characterised by the transition to the digitisation of marketing activities, emphasising the building of customer bases and the stabilisation of customer relationships. According to Kumara and Rainartze (2016), the creation of value in marketing plays a crucial role, showing a dual dimension. On one side stands the company, striving to create value for the customer, and on the other side is the customer, generating revenue for the company and having their Customer Lifetime Value (CLV). In the practical implementation of value creation for the customer, attractive advertising offering the company's products appears, capturing the customer's attention and directing them to the website. The more people engage in these actions, the more revenue and profit grow.

Interestingly, the average duration of website visits and the number of pages visited have a lesser impact on profit, although these customer actions are intertwined with website functionality and graphics. Customer behaviour in the online environment differs somewhat. E-commerce entrepreneurs should respond appropriately to customer behaviour to remain competitive and increase profits. Many authors recognise that retaining a customer is not a straightforward task.

An advantage of the online environment is its ability to collect data continuously and in a relatively long time about customers and evaluate various types of digital metrics. Companies can use these data for sales support marketing activities, dynamically adjust websites, and formulate the entire purchasing process to ensure customer satisfaction. Solutions can be sought to increase the average time spent on the website and overall visitation.

Limitations and future research

The research conducted has provided valuable insights into the factors influencing Customer Lifetime Value (CLV) in the context of e-commerce. However, it is essential to acknowledge certain limitations that may affect the generalisability and precision of the findings. First, the scope of the study was restricted by the number of examined e-commerce platforms and their respective customer bases. A more extensive sample size, encompassing a greater variety of e-shops and a more diverse customer demographic, could enhance the external validity of the results.

The set of metrics used in the research, while comprehensive, may not cover the full spectrum of factors influencing CLV. Including additional metrics, such as customer satisfaction scores, customer service interactions, or product review sentiments, could provide a more nuanced understanding and contribute to a more accurate prediction of CLV.

The time frame of the study, though sufficient to capture trends, might benefit from an extension for a more in-depth analysis of CLV evolution over time. A longer observation period would enable a more precise identification of patterns and fluctuations, contributing to a more robust analysis of customer behaviour dynamics.

Moreover, alternative mathematical and statistical methods could be explored for a more comprehensive comparison of results. Different methodologies may provide alternative perspectives, enriching the overall understanding of the relationships between variables and their impact on CLV.

Lastly, the study focused on the quantitative aspects of online marketing metrics, such as the number of visits and ad impressions. However, the qualitative aspects of online marketing communication, including the content and creativity of advertisements, were not extensively explored. A more in-depth analysis of the effectiveness of various marketing creatives and messages could offer valuable insights into optimising marketing strategies to maximise CLV.

In conclusion, while current research makes significant contributions to understanding CLV in e-commerce, acknowledging these limitations opens avenues for future research to address these aspects, refining and expanding our understanding of customer behaviour and value generation in the digital marketplace.

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