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Tatyana Shtal

Doctor of Economics, Professor
Simon Kuznets Kharkiv National University of Economics
61166, 9A Nauka Ave., Kharkiv, Ukraine
https://orcid.org/0000-0003-1256-9854

Kostiantyn Pliekhanov*

Postgraduate Student
Simon Kuznets Kharkiv National University of Economics
61166, 9A Nauka Ave., Kharkiv, Ukraine
https://orcid.org/0000-0003-4590-2836

Kyrylo Kravets

Postgraduate Student
Simon Kuznets Kharkiv National University of Economics
61166, 9A Nauka Ave., Kharkiv, Ukraine
https://orcid.org/0000-0002-3470-1919

Dmytro Bochkov

Master's Student
Simon Kuznets Kharkiv National University of Economics
61166, 9A Nauka Ave., Kharkiv, Ukraine
https://orcid.org/0000-0002-1208-8762

Trends in the development of digital subscription services in international markets

Abstract. Companies are trying to harness the potential of the current stage of development of the digital industry and make it cost-effective, which requires not only technological innovation but also the transformation of many existing business models. Based on an analysis of examples of digital subscription companies, this article provides additional explanations, including definitions and constituent characteristics of digital subscription business models. The aim of the article was to identify trends in the development of digital subscription services by analysing the number of active subscribers and the impact of COVID-19 on this indicator. Autoregression and analysis methods were used in the study, and the implementation of the selected models was carried out using the Python-3 programming language. The article describes a theoretical basis that determine the feasibility of using the subscription model for the company under non-deterministic critical conditions. The main approaches to forecasting the company's performance indicators are identified. The type of data to be forecasted is determined, and the necessity of using autoregressive models for further analysis is declared. Factors associated with the COVID-2019 incidence that should be considered as exogenous variables were identified. The multicriteria selection problem was constructed by restricting the family of autoregressive models and determining the criteria for forecasting and data preparation time, forecast accuracy, and the possibility of

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*Corresponding author

considering external factors in determining the algorithm efficiency. It is found that moving average autoregression is the most effective. Given the further application of this algorithm to predict the number of subscribers, the expediency of implementing a subscription strategy for the company under non-deterministic critical conditions is declared. It is possible to effectively apply the selected mathematical model to predict the performance of a subscription company. The practical significance of the work lies in the possibility of creating certain benchmarks for the development of the market and a business strategy for product promotion, which will be based on an understanding of the potential benefits and threats of the market for digital subscription products and services

Keywords: business model optimisation; autoregressive model; software as a service; monthly recurring revenue; number of users

INTRODUCTION

In recent years, there has been a process of increasing economic integration between countries, which leads to the merging of individual national markets into one global market, which stimulates the strengthening of the process of economy virtualisation. T. Jelassi & F. Martínez-López (2020) argued that the electronic information revolution and its product (digital economy) are changing the shape of economic relations, institutions and organisations in the global space of market economy. Therefore, it is particularly important to analyse the companies operating in this environment and identify their strategies and key success factors.

The relationship between buyers and producers has changed. Thanks to the development of the Internet and the digital world, everyone can quickly access information compare goods, services and prices. R. Kübler *et al*. (2021) point out that subscription models are becoming increasingly popular, which makes them a good way for companies to benefit from the advantages of this business model. Subscriptions offer customers more options by delivering services or products directly to their doorway and giving them the opportunity to try something without high upfront costs. Therefore, today it is possible to talk about the digital transformation of companies; in this situation, there is interest in new ways to promote a product or service through the subscription economy. C. Bagnoli *et al.* (2022) presented new digital business models in Industry 4.0 that help achieve unique competitive advantages. H. Chin *et al.* (2022) address the evolution of digital transformation in services by comparing actual use cases and published theoretical studies. Researchers W. Wang & Q. Guo (2021) studied the optimal subscription strategy for network video platforms considering social impact. P. Hanafizadeh *et al.* (2019) focused on the business model of Internet service providers at the industry level. S. Akter *et al.* (2022) examined the transformation of digital business through the prism of four emerging technology areas: artificial intelligence, blockchain, cloud, and data analytics. D. Grewal *et al*. (2019) point out in their work that the use of the Internet for business is characterized by low costs that are often covered and have a valuable offer of intangible or informative nature. Such content providers have become truly popular among consumers. Recent research in marketing has made significant progress in understanding various issues in Internet marketing, including browsing behaviour, search engine visits, and referral agents (Soegoto & Rahmansyah, 2018; Ivanechko *et al.*, 2022; Li, 2022).

Researches by economists C. Katsikeas *et al*. (2019), T.G. Lewis (2023) on information product pricing identify different pricing models that can be used to make these decisions. These include usage-based pricing, micropayments, and subscription models. The book by E.M. Noam (2019) examines in detail various aspects of digital organisation, including pricing issues. L. Rainsberger (2023) examined the current state of digital sales technology and tools, focusing on processes from positioning to customer management throughout the sales strategy. K. Sato & K. Nakashima (2020) addressed the consequences of competitive equilibrium when the same electronic goods are offered at different pricing policies. The share of online companies offering their services by subscription is slowly but steadily increasing. Given the growth of the global economy and the growing demand for fast and effective solutions, the operating principles of work of subscription companies will spread to other areas of life. B.W. Wirtz (2021) proved that simultaneously with the growing demand for such programs, the methods of data analysis to improve the work with consumers will also increase. This will provide the opportunity to optimise processes to understand what works and what does not work in this online business. Provided that the needs of consumers are met qualitatively, companies will thrive and offer their founders the opportunity to constantly increase their revenues. The relevance of the study is determined by the increasing role and market share of digital products in the international market and the significant potential of the digital products market as one of the driving factors for the development of the economy. Therefore, the aim was to examine trends in the development of digital subscription services, taking into account the number of active subscribers and the impact of COVID-19 on this indicator.

MATERIALS AND METHODS

In order to properly select categories for analysis, a set of axiomatic rules was defined. Firstly, the companies under study must adhere in their policies to the model of unrestricted use at fixed rates. Secondly, business segments and company sizes are differentiated by income and number of employees. Thirdly, only companies that have a competitive advantage due to their subscription strategy are considered. The number of subscribers can be used in forecasting indicators of companies' business activities. In this study, autoregressive models were used as a baseline. The autoregressive model can be presented as follows:

$$\Phi_0 y_t = \Phi_1 y_{t-1} + \cdots + \Phi_p y_{t-p} + \Theta_0 u_t + \Theta_1 u_{t-1} + \cdots + \Theta_q u_{t-q}, \quad (1)$$

where y_t is the K-dimensional time series; Φ_i, Θ_j is the K×K matrices, $\overline{i=1,\ p}$, $\overline{j=1,\ q}$; u_t is the K-dimensional white noise vector with zero mean and non-degenerate covariance matrix $\Sigma = E(u_t, u_t')$. It should be noted that Φ_0 and Θ_0 are non-degenerate matrices, therefore, they can be normalized to 1. Since it is proposed to take into consideration the effects of the dynamics of coronavirus infection, this model should be modified, as it does not allow for exogenous variables. To do so, $\Phi_0 y_{t-1}$ needs to be substracted from the right and left parts of the given equality:

$$\Phi_0 \Delta y_t = \prod y_{t-1} + \Psi_1 \Delta y_{t-1} + \cdots + \Psi_{p-1} y_{t-p+1} + \Theta_0 u_t + \\ + \Theta_1 u_{t-1} + \cdots + \Theta_q u_{t-q}, \quad (2)$$

where $\prod = -(\Phi_0 - \Phi_1 - \cdots - \Phi_p)$; $\Psi_i = -(\Phi_{i+1} + \cdots + \Phi_p)$ $\overline{i=1,\ p-1}$. This formula (2) is a generalized representation of the whole family of autoregression models, which includes the following models: autoregression (AR); seasonal autoregression (SAR); autoregression of distributed lags (ARDL); autoregression of moving average (ARMA). In order to determine the most effective model in the framework of the proposed study, the statement of the criteria selection problem should be developed. As a first step (the set of alternatives has already been selected), it is necessary to determine the comparison criteria: algorithm runtime; forecast accuracy; completeness of consideration of exogenous variables; data preparation time. The forecast accuracy was measured in whole percentages and can take values between 0 and 100. To make the result more objective, the algorithms should be applied to Netflix and Amazon Prime data to forecast the number of subscribers for 2023. The time indicator was measured in seconds (s), and it was later converted into time savings so that all indicators relate to the same optimisation function (maximum). To avoid problems related to a measurement error, 5 time measurements were performed. To be able to use a qualitative indicator of the completeness of consideration of exogenous variables, the following scale was introduced: exogenous variables are not considered – 0 points; exogenous variables are partially considered – 1 point; exogenous variables are fully considered – 2 points. To implement autoregression models and to check their accuracy and runtime, the Python programming language was used, in particular such libraries as: numpy, scikit-learn, pandas.

After measurements, the determination of the most effective model from the selected family was carried out according to the principle of linear additive convolution with weighting coefficients, with the time indicators replaced by the time-saving indicators and a score assigned to each criterion. After these measures, the alternatives are eliminated using the Pareto principle (those that have values for all the criteria no higher than any of the other alternatives may not be considered). Given the importance of the accuracy indicator and the possibility of considering external factors, the following is noted (with the time indicators being roughly equal in value): accuracy – 4 points; consideration of external factors – 4 points; forecast time saving – 1 point; preparation time saving – 1 point. The following weighting factors: accuracy – 0.4; consideration of external factors – 0.4; forecast and preparation time saving – 0.1.

RESULTS AND DISCUSSION

The experimental results obtained are described below. The accuracy results are presented in Table 1. The average value for AR is 85%, for SAR – 89%, for ARDL – 88%, for ARMA – 95%. Thus, the moving average algorithm for the selected datasets shows greater accuracy.

Table 1. Result of accuracy measurements

Data	AR	SAR	ARDL	ARMA
Netflix	83%	89%	86%	94%
Amazon Prime	87%	88%	90%	95%

Source: made by the authors

This can be explained by the existing possibility of considering the volatility of indicators using an average value between neighbouring training learning variables and a broader spectrum of considering exogenous variables in the forecast. The results for the runtime data are shown in Table 2.

Table 2. Result of forecast time measurements

AR	SAR	ARDL	ARMA
0.039 s	0.064 s	0.073 s	0.088 s
0.043 s	0.069 s	0.087 s	0.092 s
0.059 s	0.073 s	0.078 s	0.086 s
0.067 s	0.077 s	0.074 s	0.095 s
0.075 s	0.069 s	0.082 s	0.086 s

Source: made by the authors

The average values for AR are 0.057 s, for SAR – 0.070 s, for ARDL – 0.079 s, for ARMA – 0.089 s. The relatively slow speed of the ARMA algorithm, which was the most accurate, is explained by the need for additional calculations of the neighbouring averages. Instead, the AR algorithm is algebraically and informationally the simplest (it uses the least number of mathematical operations for accessing the memory), thus it shows the best results for the runtime. The data for the preparation time are shown in Table 3.

Table 3. Result of data preparation time measurements

AR	SAR	ARDL	ARMA
0.012 s	0.022 s	0.025 s	0.039 s
0.011 s	0.025 s	0.023 s	0.040 s
0.013 s	0.019 s	0.018 s	0.029 s
0.012 s	0.024 s	0.023 s	0.026 s
0.011 s	0.027 s	0.021 s	0.035 s

Source: made by the authors

The average values for AR are 0.012 s, for SAR – 0.023 s, for ARDL – 0.023 s, for ARMA – 0.034 s. These dynamics in the preparation time is explained by the fact that the SAR, ARDL, and ARMA algorithms require exogenous variables that must also be processed. However, ARMA can use external indicators more frequently than the others. The non-zero time of data preparation for AR is explained by the need to check the training sample for outliers, empty values converted to an average, etc. Table 4 is formed with the criteria data for each model. The time indicators are replaced with the time-saving indicators (Table 5).

Table 4. Criteria values

	Forecast time	Accuracy	Consideration of external factors	Preparation time
AR	0.057 s	85%	0	0.012 s
SAR	0.070 s	89%	1	0.023 s
ARDL	0.079 s	88%	1	0.023 s
ARMA	0.089 s	95%	2	0.034 s

Source: made by the authors

Table 5. The criteria values are reduced to the same optimisation principle

	Forecast time saving	Accuracy	Consideration of external factors	Preparation time saving
AR	0.032 s	85%	0	0.022 s
SAR	0.019 s	89%	1	0.011 s
ARDL	0.010 s	88%	1	0.011 s
ARMA	0.000 s	95%	2	0.000 s

Source: made by the authors

To reduce the number of possible alternatives, the Pareto principle was applied. According to it, the ARDL alternative can be excluded, since all the indicators for it are lower than or equal to the SAR alternative. Table 6 shows the Pareto-optimal alternatives. Now the time criteria have to be normalized, taking into account that there are no reference values for them. The best value for the forecast time saving is 0.032 s, the worst is 0 s. For SAR: 0.019/0.032 = 0.59. The best value for the preparation time saving is 0.022 s, the worst is 0 s. For SAR: 0.011/0.022 = 0.5. In precision, the reference value is 100, and for the consideration of external factors – 2. The following normalized values are shown in Table 7.

Table 6. Pareto-optimal alternatives

	Forecast time saving	Accuracy	Consideration of external factors	Preparation time saving
AR	0.032 s	85%	0	0.022 s
SAR	0.019 s	89%	1	0.011 s
ARMA	0.000 s	95%	2	0.000 s

Source: made by the authors

Table 7. Normalized values

	Forecast time saving	Accuracy	Consideration of external factors	Preparation time saving
AR	1	0.85	0	1
SAR	0.59	0.89	0.5	0.5
ARMA	0	0.95	1	0

Source: made by the authors

Using the predetermined weighting factors, the value of the selected convolution can be found.

For AR: $0.1 + 0.85 \times 0.4 + 0.1 = 0.54$.

For SAR: $0.1 \times 0.59 + 0.89 \times 0.4 + 0.5 \times 0.4 + 0.5 \times 0.1 = 0.67$

For ARMA: $0.95 \times 0.4 + 0.4 = 0.78$

Thus, it can be argued that the moving average autoregression model is the most effective within the proposed subject area. It is necessary to present the obtained results of this model, starting with the parameters. For the Netflix data, the following model parameters are presented in Figure 1.

	coef	std err	z	P>|z|	[0.025	0.975]
const	104.1840	161.005	0.647	0.518	-211.381	419.749
x1	0.0030	0.002	1.772	0.076	-0.000	0.006
ar.L1	0.9953	0.048	20.767	0.000	0.901	1.089
ma.L1	0.8331	0.185	4.494	0.000	0.470	1.196
ma.L2	0.4437	0.122	3.642	0.000	0.205	0.682
sigma2	13.0820	4.720	2.771	0.006	3.830	22.333

Figure 1. Model parameters for Netflix
Source: made by the authors

From the result, it can be seen that the direct base data are the most influential, their moving average is not so influential, which is due to the insignificant volatility of the number of subscribers. In this case, the forecast result is as follows (Fig. 2). Q1 2022: 222 million people – the real value is 222; Q2 2022: 223 million people – the real value is 221; Q3 2022: 225 million people – the real value is 223; Q4 2022: 229 million people – the company's forecast value is 224. For the Amazon Prime data, the following set of coefficients was obtained (Fig. 3). In this case, the impact of the base data is even larger. The result of the research is as follows (Fig. 4). Q1 2022: 155 million people – the real value is 153; Q2 2022: 156 million people – the real value is 153; Q3 2022: 158 million people – the real value is 155; Q4 2022: 160 million people – the company's forecast value is 157. Thus, it can be concluded that during this time period, an external factor such as the COVID-19 pandemic did not significantly affect the number of Netflix and Amazon Prime subscribers, and the overall trend persisted. Taking into consideration the obtained mathematical models, it is possible to make a forecast of the number of subscribers for the four quarters of 2023 (Table 8).

It should be noted that the obtained results are based on the forecast of the average number of COVID-19 diseases per quarter, which may lead to an increase in the error of the forecast data. According to the results of the study, it can be concluded that the existing business strategies in the selected companies are effective in maintaining and increasing the number of active subscribers. The efficiency in the present study meant the value of the linear additive convolution with the weighting coefficients for accuracy indicators, time saving in forecasting and data preparation, and the possibility of considering the impact of external factors. The findings from the research could be applied in various ways. One potential use is the creation of a customized pricing strategy. Additionally, the algorithm could serve as an integral component of a decision support system, offering both passive and active support to help companies reduce risks when employing a subscription model in circumstances like those experienced during the pandemic.

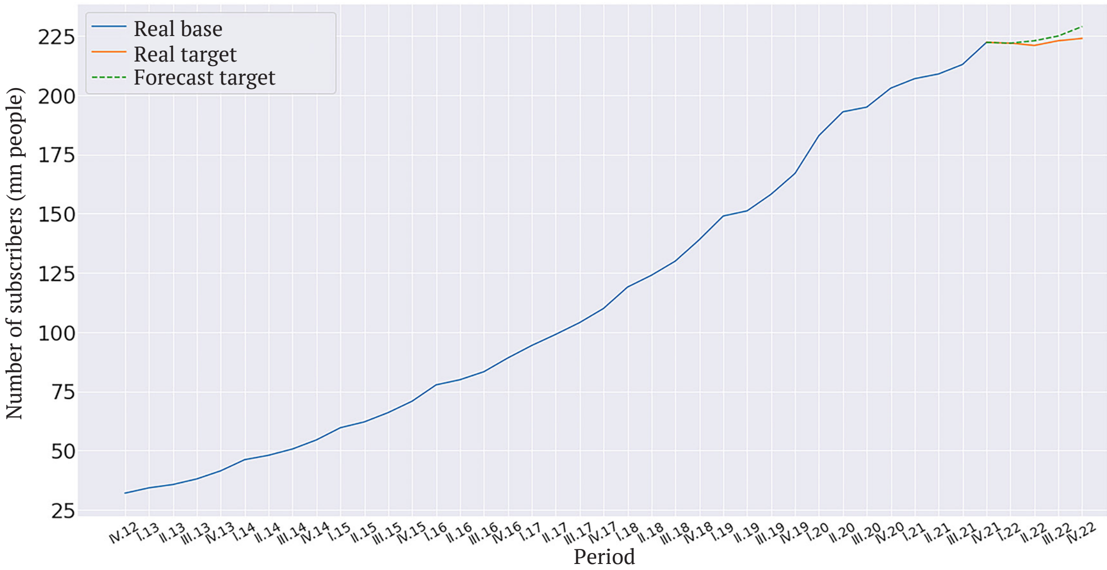

Figure 2. Forecast result for Netflix

Source: made by the authors based on Statista (n.d.)

	coef	std err	z	P>|z|	[0.025	0.975]
const	78.6722	82.730	0.951	0.342	-83.476	240.820
x1	0.0011	0.002	0.696	0.486	-0.002	0.004
ar.L1	0.9958	0.029	33.944	0.000	0.938	1.053
ma.L1	0.7360	0.286	2.569	0.010	0.175	1.297
ma.L2	0.9764	0.707	1.381	0.167	-0.410	2.363
sigma2	5.0784	3.602	1.410	0.159	-1.982	12.139

Figure 3. Model parameters for Amazon Prime

Source: made by the authors

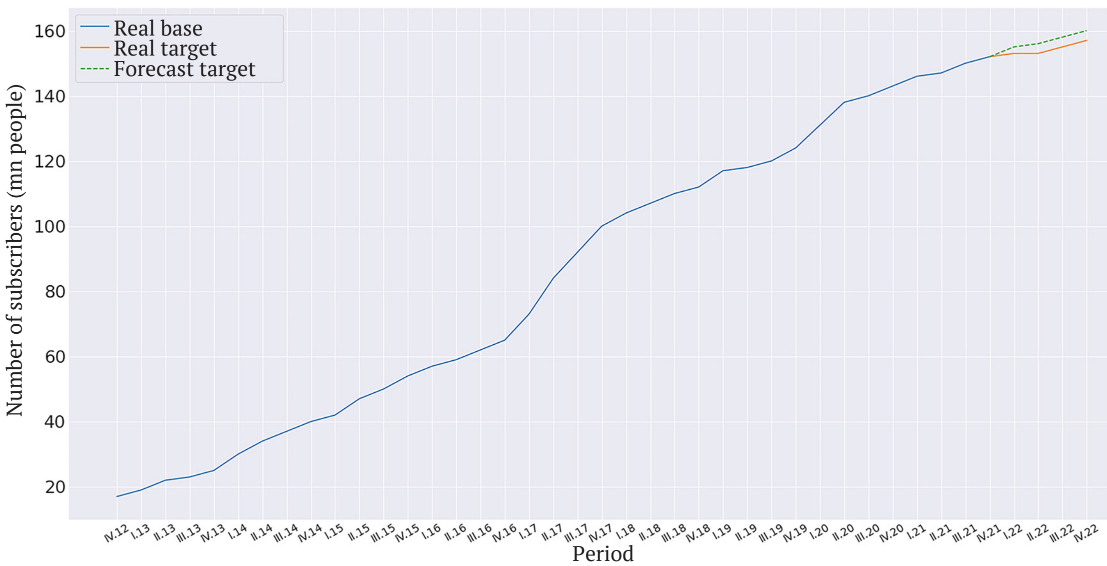

Figure 4. Forecast result for Amazon Prime

Source: made by the authors

Table 8. Forecast of the number of subscribers

	Q1, 2023	Q2, 2023	Q3, 2023	Q4, 2023
Netflix	229 mn people	234 mn people	238 mn people	241 mn people
Amazon Prime	164 mn people	168 mn people	168 mn people	174 mn people

Source: made by the authors

It should be noted that the problematics related to predicting the number of subscribers with autoregressive models is new, but this class of models has been applied by M. Nkongolo (2023) to study the volume of user data; in this work, he proved the feasibility of using the selected family of algorithms when dealing with extensive data related to users of subscription services. I. Ullah *et al.* (2019) point out in their study that machine learning is quite sensitive to the amount of data, and since this type of service has been spreading for a relatively short time, it is quite a complex process to obtain a satisfactory result, even after data augmentation. The probabilistic approach is used in cases where the external conditions are relatively stable and do not significantly affect the overall result, as stated by P. Ghosh *et al.* (2021). Taking into account that the data were affected first by the crisis triggered by the pandemic and then by the general political instability due to the Russian Federation's full-scale invasion of Ukraine, this approach may also be considered inexpedient.

In addition to the above, using autoregression to predict indicators of business activity (which include the number of subscribers) during significant social changes caused by emergency situations, which include the COVID-19 pandemic, generally yields a 95% result accuracy, according to the study by A. Khovrat *et al.* (2022). In this research, the moving average autoregression algorithm was determined as the most effective. It should be noted that, compared to the research mentioned, to predict the number of subscribers without considering polymorphic data, additional constraints need to be introduced to the selection of the target companies, which were mentioned earlier. When these constraints are removed, there is a significant risk of obtaining a less accurate forecast, but the use of more exogenous variables, especially those not directly related to the pandemic, is beyond the scope of the present study.

The selected exogenous variables that are indicators of COVID-19 were studied by P. Congdon (2021), who not only showed the possibility of effective use of autoregression to forecast the dynamics of incidence rates, but also examined the issue of including these data as external factors influencing business development in general and their digital strategies in particular. Similar results were obtained by scholars E. Karaçuha *et al.* (2020) from Istanbul Technical University and B. Buru & M. Gursoy (2022) from Koçu University. It should also be mentioned here that separate approaches, which may include, for example, expert evaluation or logistic regression, must be used in selecting additional external factors. According to the work of A. Khovrat *et al.* (2022), the first of the approaches has proven its effectiveness regarding the outlined problematics, while the second has found its confirmation in the context of various tasks, as noted by J. Wang *et al*. (2023).

Regarding other algorithms for forecasting the number of subscribers, it is worth mentioning the work of a scholar from the University of Toronto in Canada, B.W. Wirtz (2021), on the application of multidimensional linear regression. The author of the article notes that despite the fairly accurate results of the forecast, there is the problem of high sensitivity to outliers. Similar results were also obtained by Q. Yan (2022) from the University of Sydney, who studied the issues of forecasting subscription prices for Netflix. In view of all the above mentioned points, it can be argued that the selected approaches, methods, and exogenous variables were selected in accordance with international scientific practices. The findings do not contradict recognised scientific studies.

CONCLUSIONS

The study has proved that the digital economy includes economic activities involving millions of daily online communications between people and businesses, which means the growing need of people and organisations for information exchange that is only possible through the Internet, mobile technologies, etc. The use of the family of autoregressive models to forecast the number of active users allows to assert the overall effectiveness of using the subscription model under non-deterministic critical conditions. Four autoregressive models were considered in the study: autoregression; seasonal autoregression; autoregression of distributed lags; autoregression of moving average. Given the number of new COVID-19 cases in the proposed time frame, among the algorithms of this family that showed an accuracy of 85% to 95% on the test data provided by Amazon and Netflix, the moving average algorithm is the most effective. The efficiency factors selected were: saving forecast time, saving preparation time, accuracy, and the possibility of considering exogenous variables. Among these factors, the ARMA model is the slowest of the proposed models, but this shortcoming is compensated by the accuracy, which is the most important indicator in case of crisis.

In addition to providing practical confirmation of the feasibility of using the subscription model under non-deterministic critical conditions, the present study examined the theoretical basis that would determine the effectiveness of this strategy. The constraints imposed on the target data of the company were determined, which allowed to obtain a more accurate result. The results obtained in the study can be used, for example, to develop an own pricing strategy. Another possible application is the use of this algorithm as part of a decision support system, both passive and active, which would mitigate the risks for companies using the subscription model in situations similar to COVID-19. Since only basic autoregressive models, which are quite sensitive to external factors and outliers in target time series, were considered for the present work, it was decided to leave for further research the issue of reducing the impact of outliers and missing target data as well as their augmentation. The latter is due to the fact that the data on the number of subscribers are usually reported in open sources on a quarterly basis; thus, to present them correctly on a weekly scale, it is necessary to use separate methods.

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CONFLICT OF INTEREST
None.

REFERENCES
[1] Akter, S., Michael, K., Uddin, M.R., McCarthy, G., & Rahman, M. (2022). Transforming business using digital innovations: The application of AI, blockchain, cloud and data analytics. *Annals of Operations Research*, 308, 7-39. doi: 10.1007/s10479-020-03620-w.

[2] Bagnoli, C., Albarelli, A., Biazzo, S., Biotto, G., Marseglia, G.R., Massaro, M., Messina, M., Muraro, A., & Troiano, L. (2022). *Digital business models for Industry 4.0. How innovation and technology shape the future of companies*. Cham: Springer. doi: 10.1007/978-3-030-97284-4.

[3] Buru, B., & Gursoy, M.E. (2022). Forecasting daily COVID-19 case counts using aggregate mobility statistics. *Data*, 7(11), article number 166. doi: 10.3390/data7110166.

[4] Chin, H., Marasini, D.P., & Lee, D. (2022). Digital transformation trends in service industries. *Service Business*, 17, 11-36. doi: 10.1007/s11628-022-00516-6.

[5] Congdon, P. (2021). COVID-19 mortality in English neighborhoods: The relative role of socioeconomic and environmental factors. *Multidisciplinary Scientific Journal*, 4(2), 131-146. doi: 10.3390/j4020011.

[6] Ghosh, P., Neufeld, A., & Sahoo, J.K. (2021). Forecasting directional movements of stock prices for intraday trading using LSTM and random forests. *Finance Research Letters*, 46, article number 102280. doi: 10.1016/j.frl.2021.102280.

[7] Grewal, D., Hulland, J., Kopalle, P.K., & Karahanna, E. (2019). The future of technology and marketing: A multidisciplinary perspective. *Journal of the Academy of Marketing Science*, 48(1), 1-8. doi: 10.1007/s11747-019-00711-4.

[8] Hanafizadeh, P., Hatami, P., & Bohlin, E. (2019). Business models of internet service providers. *Netnomics*, 20, 55-99. doi: 10.1007/s11066-019-09130-7.

[9] Ivanechko, N., Dudar, V., & Pavelko, V. (2022). Search engine marketing. *Galician Economic Journal*, 74(1), 158-162. doi: 10.33108/galicianvisnyk_tntu2022.01.158.

[10] Jelassi, T., & Martínez-López, F. (2020). *Strategies for e-business concepts and cases on value creation and digital business transformation*. Cham: Springer. doi: 10.1007/978-3-030-48950-2.

[11] Karaçuha, E., Önal, N.Ö., Ergün, E., Tabatadze, V., Alkaş, H., Karaçuha, K., Tontuş, H.Ö., & Nu, N.V.N. (2020). Modeling and prediction of the COVID-19 cases with deep assessment methodology and fractional calculus. *IEEE Access*, 8, 164012-164034. doi: 10.1109/ACCESS.2020.3021952.

[12] Katsikeas, C., Leonidou, L., & Zeriti, A. (2019). Revisiting international marketing strategy in a digital era: Opportunities, challenges, and research directions. *International Marketing Review*, 37(3), 405-424. doi: 10.1108/IMR-02-2019-0080.

[13] Khovrat, A., Kobziev, V., Nazarov, A., & Yakovlev, S. (2022). Parallelization of the VAR algorithm family to increase the efficiency of forecasting market indicators during social disaster. In *Information technology and implementation (IT&I-2022)* (pp. 222-233). Kyiv: CEUR Workshop Proceedings.

[14] Kübler, R., Seifert, R., & Kandziora, M. (2021). Content valuation strategies for digital subscription platforms. *Journal of Cultural Economics*, 45, 295-326. doi: 10.1007/s10824-020-09391-3.

[15] Lewis, T.G. (2023). Digital economy: The economics of the digital economy. *Ubiquity*, 2023(4), article number 1. doi: 10.1145/3594560.

[16] Li, D. (2022). Observation and speculation of new internet marketing. *BCP Business & Management*, 29, 112-116. doi: 10.54691/bcpbm.v29i.2196.

[17] Nkongolo, M. (2023). Using ARIMA to predict the growth in the subscriber data usage. *Eng*, 4(1), 92-120. doi: 10.3390/eng4010006.

[18] Noam, E.M. (2019). *Managing media and digital organizations*. Cham: Palgrave Macmillan. doi: 10.1007/978-3-319-71288-8.

[19] Rainsberger, L. (2023). *Digital transformation in sales. How to turn a buzzword into real sales practice – a 21-step guide*. Wiesbaden: Springer.

[20] Sato, K., & Nakashima, K. (2020). Optimal pricing problem for a pay-per-use system based on the internet of things with intertemporal demand. *International Journal of Production Economics*, 221, article number 107477. doi: 10.1016/j.ijpe.2019.08.012.

[21] Soegoto, E.S., & Rahmansyah, M.R. (2018). Use of internet as product marketing media using internet marketing method. *IOP Conference Series: Materials Science and Engineering*, 407, article number 012053. doi: 10.1088/1757-899x/407/1/012053.

[22] Statista. (n.d.). Retrieved from https://www.statista.com/.

[23] Ullah, I., Raza, B., Malik, A.K., Imran, M., Islam, S.U., & Kim, S.W. (2019). A churn prediction model using random forest: Analysis of machine learning techniques for churn prediction and factor identification in telecom sector. *IEEE Access*, 7, 60134-60149. doi: 10.1109/ACCESS.2019.2914999.

[24] Wang, J., Wang, H., Nie, F., & Li, X. (2023). Feature selection with multi-class logistic regression. *Neurocomputing*, article number 126268. doi: 10.1016/j.neucom.2023.126268.

[25] Wang, W., & Guo, Q. (2023). Subscription strategy choices of network video platforms in the presence of social influence. *Electronic Commerce Research*, 23, 577-604. doi: 10.1007/s10660-021-09504-w.
[26] Wirtz, B.W. (2021). *Digital business and electronic commerce. Strategy, business models and technology*. Cham: Springer. doi: 10.1007/978-3-030-63482-7.
[27] Yan, Q. (2022). The stock price analysis of Netflix prediction. *BCP Business & Management*, 34, 964-968. doi: 10.54691/bcpbm.v34i.3117.

Тетяна Валеріївна Шталь
Доктор економічних наук, професор
Харківський національний економічний університет імені Семена Кузнеця
61166, просп. Науки, 9А, м. Харків, Україна
https://orcid.org/0000-0003-1256-9854

Костянтин Володимирович Плєханов
Аспірант
Харківський національний економічний університет імені Семена Кузнеця
61166, просп. Науки, 9А, м. Харків, Україна
https://orcid.org/0000-0003-4590-2836

Кирило Олександрович Кравець
Аспірант
Харківський національний економічний університет імені Семена Кузнеця
61166, просп. Науки, 9А, м. Харків, Україна
https://orcid.org/0000-0002-3470-1919

Дмитро Романович Бочков
Магістрант
Харківський національний економічний університет імені Семена Кузнеця
61166, просп. Науки, 9А, м. Харків, Україна
https://orcid.org/0000-0002-1208-8762

Тенденції розвитку цифрових підписних сервісів на міжнародних ринках

Анотація. Компанії намагаються використати потенціал сучасного етапу розвитку цифрової індустрії та зробити його економічно вигідним, для чого необхідні не лише технологічні інновації, а й трансформація багатьох існуючих бізнес моделей. Базуючись на аналізі прикладів цифрових підписних компаній, ця стаття надає додаткові роз'яснення, зокрема визначення та складові характеристики бізнес моделей передплати в цифрових сервісах. Метою статті було виявлення тенденцій розвитку цифрових підписних сервісів на основі аналізу кількості активних підписників та впливу COVID-19 на цей показник. У дослідженні були використані методи авторегресії та аналізу, імплементація обраних моделей здійснена мовою програмування Python-3. Описано теоретичне підґрунтя, яке зумовлює доцільність використання підписної моделі для компанії в недетермінованих критичних умовах. Визначено основні підходи до прогнозування показників діяльності компанії. Встановлено характер даних, що прогнозуватимуться, декларовано необхідність використання авторегресійних моделей для подальшого аналізу. Визначено фактори пов'язані із захворюваністю COVID-19, які варто врахувати як екзогенні змінні. Здійснено побудову задачі багатокритеріального вибору шляхом обмеження сімейства авторегресійних моделей та визначення критеріїв часу прогнозування і підготовки даних, точності прогнозу і можливості врахування зовнішніх факторів при знаходженні ефективності алгоритму. Визначено, що найбільш ефективною є авторегресія рухомого середнього. З огляду на подальше застосування вказаного алгоритму для прогнозування кількості підписників, декларується доцільність реалізації підписної стратегії для компанії в недетермінованих критичних умовах. Передбачається можливість ефективного використання обраної математичної моделі для прогнозування показників діяльності компанії, що працює за передплатою. Практичне значення роботи полягає у можливості побудови певних орієнтирів для розвитку ринку та розробки бізнес стратегії просування продукту, які базуватимуться на розумінні можливих переваг та загроз, які має ринок цифрових підписних продуктів та сервісів

Ключові слова: оптимізація бізнес-моделі; авторегресійна модель; програмне забезпечення як послуга; щомісячний регулярний дохід; кількість користувачів