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MANAGEMENT OF PHARMACEUTICAL ONLINE RETAIL THROUGH A REGIONAL MARKETPLACE WITH NEURAL NETWORK AND STATISTICAL ANALYTICAL TOOLS

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The study is devoted to applying neural networks and statistical analytical tools for the estimation of efficiency of pharmaceutical retail. The empirical basis was data derived from the Ukrainian regional online marketplace. The article proposes and tests approach to analytical decision-making in online retail, which involves combining several clustering and forecasting models and methods, complementing each other accordingly. Analysis of the results of clustering and statistical processing of empirical datasets characterizing customer orders for goods in pharmacies, as well as the order-placement procedure, made it possible to identify patterns in the behaviour of customers and pharmacy staff in the process of fulfilling orders. We also created a perceptron-type neural network to predict the value of sold products as the final result of each commercial operation in a pharma store. The modelling results form the necessary conditions for determining management indicators and assessing the effectiveness of interactions with customers, which have practical value and potentially allow increasing sales and customer service levels.

Keywords: *online retail, pharmacy, consumers' behaviour, Kohonen mapping, perceptron-type neural network, clustering, forecasting, commercial performance*

JEL Classification: C15, C38, C45, L81, M21, M31

Introduction

Nowadays dynamic social and economic changes significantly increase the volatility and unpredictability of business processes on different levels. Numerous external and internal factors should be taken into account by decision-makers on national, regional and corporate levels. Managers of companies involved in commercial and logistics operations are not exceptions and every day have to assess qualitative and quantitative parameters aiming at the desired profit. Partially, a solution to this issue can be found in famous and popular methods of business management (administration) like cost optimization, demand forecasting, budget planning etc.

Obviously, the real business practice around the globe is more diverse, usually more complicated and integrates business functions not only within one business entity (company, group of companies, association etc.), but also provides outsourcing to external partners. Two opposite forces stimulate the development of commercial and managerial mechanisms on the corporative level – competitive differentiation and global integration. These both have significant implications on various social and economic processes but, obviously, they lead to the dialectical contradiction – how to get stable competitive uniqueness together with efficient integration of business processes with partners and consumers.

Commerce and trade as general and natural parts of almost all profit-oriented businesses is under influence of the above-mentioned processes and is changing constantly mirroring more global impacts. The rocketed development of the commercial technologies pushed by IT progress should be grounded on the relevant growth of the internal ability of companies to manage more and more complicated situations, processes and sub-systems. The huge amount of the raw data generated by modern gadgets and numerous web applications creates additional opportunities for tracing consumers' behaviour, aggregating various data sets, which opens up space for innovations.

The growth of available information in commerce is accompanied by the increasing dynamic of decision-making. It means that corporative managers have fewer and fewer opportunities to work on their decisions without time pressure, should use more advanced tools for analytical justification of their choices etc. On another hand, not all decisions really need to be grounded on the precise analysis that is also time-consuming process. Therefore, the problem of how to re-establish or modernize managerial mechanisms in companies today has significant value both from theoretical and practical points of view.

Analysis of recent research and publications

Considering specific of pharma goods as a trade objects, the development of managerial practices in the area of e-commerce and online retail in the pharmaceutical industry has become a demanding topic over last years. The scientific efforts around the globe mainly focus on two conceptual directions: business administration and management of e-commerce projects; data mining and modelling of consumers' online behaviour. The current paper addresses the objectives of both blocks of scientific works.

X. Zhang et al. [1] considered online operations via corporative websites and developed data mining tools to identify customer Internet browsing patterns. They employed Kohonen Self-Organizing Map (SOM) for describing target audiences' profiles and identifying the most efficient a set of tools of engaging individual users. The authors demonstrated that neural networks could be used to produce valuable recommendations for managers. E. Bradlow et al. [2] worked on finding ways of combining blended user data sources for decision-making under the big data generation on the Internet. They claimed the importance of predictive modelling to improve efficiency of retail operations with particular focus on Bayesian analysis techniques.

A. Sulthana and S. Ramasamy published the study [3] devoted using neuro-fuzzy classification where they proposed a recommendation system based on users' reviews. This approach automatically classifies the reviews under the respective fuzzy rules and it was announced as an effective managerial tool.

M. Nilashi et al. [4] presented study of customer decision-making based on their ratings on retailing web-sites. The main conclusions of their paper was about the Multi-criteria Collaborative Filtering that can predict the most relevant products to users. In this paper, the authors especially highlight the problem of data sparsity and solve it using SOM and Expectation Maximizing clustering techniques.

S.-H. Liao et al. [5] explored the topic of mining customer knowledge for product line and brand extension in retailing, created a background for identifying significance of the primary, secondary and generic branding in retail. To this end, they applied Apriori algorithm for association rule learning and k-means for cluster analysis.

The paper [6] is devoted to investigating advertising prices and advertising strategies for the company's major products. The relevance of advertising strategies to goals, ad placement, message creation, budget constraints, and ad delivery is determined. When analyzing advertisement efficiency, European countries are segmented using the Data Envelopment Analysis model.

In the article [7] first an assessment of the state of enterprises and their position in the market is carried out based on a set of quantitative and qualitative characteristics using fuzzy logic tools, which allows the use of SWOT analysis to formulate a marketing strategy.

SWOT analysis in combination with fuzzy methods of multi-criteria evaluation were also applied in the paper [8] to stratification of possible enterprise strategies and their selection depending on the prevailing conditions. Fuzzy inference system based on Mamdani method was proposed by M. Kokoç et al. [9] to evaluate marketing strategies and their inherent risk in determining target markets and types of products to be introduced to the market.

K. Leung et al. [10] addressed their research to operating efficiency under the complexity of today's e-commerce environment. They focused on logistics as a crucial part of competitive advantages of companies in the e-commerce. In line with this general task, the authors suggested an approach and developed an integrated Auto-regressive-Adaptive Neuro-Fuzzy Inference System for forecasting e-commerce order arrivals. This publication is also valuable for our research, especially regarding the forecasting e-order arrivals.

The work of M. Malhotra et al. [11] is dedicated to structuring complex objects in management. If conditions are highly uncertain, the researchers propose integrating five classification methods: discriminant analysis, quadratic discriminant analysis, neural networks, multinomial logistic regression analysis, and k-nearest neighbours algorithm. The effectiveness of the approach was confirmed by its practical application in decision-making systems.

The different approach was presented by S. Rodrigues and G. Serra [12], starting from statistical time series forecasting based on Spectral Analysis and Evolving Neuro-Fuzzy Network to assist managerial decisions' development. It would be also beneficial to mention the study by Ch. Wang [13] on the topic of efficient customer segmentation in digital marketing using deep learning with swarm intelligence approach. In this research, customers are clustered using self-organizing map, based on which they are classified using the deep neural network model. The author derived valuable conclusion about customer behaviour and correlation of purchasing patterns with generated profit for the company.

Cluster methods are actively used to solve other marketing problems as well. The group of scientists R. Kuo et al. [14] proposed a two-stage method to market segmentation, which first uses self-organizing maps to determine the number of clusters and initial approximation, and then uses genetic k-means algorithm to find the final solution. Basically, the study used the freight transport industry market data, but it is also valuable for the pharmaceutical online retail.

The article [15] presents the approach of applying cluster analysis to classify customers and scoring models to predict customer churn when making management decisions on retaining existing customers and acquiring new ones. O. Savych et al. [16] also proposed a two-level approach to solving the task of forecasting car sales in the European market, which consists of clustering with the construction of forecast models based on indicators characterizing the automobile market in the world as a whole, as well as in the context of individual parts of the world or clusters.

The study by S. France and S. Ghose [17] explored different tools and approaches to marketing analytics with implementing them for solving tasks of visualization, segmentation, and class prediction. Their study offered an overview of marketing analytic tools providing a good initial point for the interdisciplinary interpretation of our research.

Overall, the broad scope of already existing applications of business practices allows us to conclude the followings regarding pharma online retail management:

– The AI is becoming more and more regularly used in the scientific research in different areas, and the models developed are targeting broad range of application and behavioural cases. At the same time, given the huge variety of products, types of sales, and specifics of clients in marketing tasks, a large number of researches are focused on clustering the general data set and further analysis and work with each selected segment separately.

– Bias or irrational behaviour observed in the modern markets decreases the feasibility of the classical economic analysis. At the same time, the scope of the significant factors and available data sets stimulate researches of decision-making under fuzzy or unidentified conditions [18].

– Speed and time-adjusted decisions become more and more important for commercial success in retail, while low levels of competition and consumers' differentiation are shorting chances to implement already approved commercial strategies.

– Ideally, the retail management system should be able to evaluate the results of the previously made decision and minimize mistakes in the future. Thus, the deep learning models and various smart decision systems are prioritized in the digital marketing area.

Results

The starting point of our research is a clarification of the managerial control model. This approach is suitable for a wide range of managerial problems in real business practice and can build ground for the assessment of sale decision.

The empirical part of the study is based on the data set of the 115 pharmaceutical stores that are listed on the Ukrainian local marketplace "Tabletki.ua" (https://tabletki.ua/). It should be noticed, that the selected marketplace doesn't provide full commercial cycle, but just reserve a product in a pharma store with the special discount for a customer, and the final stage – a trade operation and payments – will be done when the client visits the pharma store by its cash-desk.

We had extracted a sample of 3672 observations and the following list of the variables only for the 3 days:

– Pharmaceutical stores with addresses – based on this information the variable "Pharma store ID" was created for unique identification of all units in our sample.

– Date – this variable was not used much due to the limited time frame (only 3 days) and goals of our research.

– Delay in processing consumer request after the request was received (HH:MM:SS) – information about what time was needed for responding to a received customer’s request of the pharma product in a selected pharma store. On the basis of this info the variable “Time of response” (time of response in seconds) was created by transferring hours and minutes into seconds.

– The cost of requests (UAH) received in one customer order in a selected pharma store allowed us to create the variable “Value of request”. The software of the marketplace fixed this info automatically.

– Value of the sold products (UAH) was also fixed automatically as variable “Value sold” after the customer paid the product in a pharma store. This indicator presents the actual value of sold goods out of the total value of ordered ones. Technically, after each payment, the seller (manager) closes the request received via the marketplace.

– Extra delta (result - request) received (UAH). This is difference between value of requested products and value of sold products, and it can be formed by various reasons. The customer can face the problem of price difference via the marketplace and in the pharma store. We estimated this indicator “Extra sales” based on the data of the sample and can mention that 12.45% of all requests were closed with differences.

– The data set includes information about status of a customer’s order. So, we consider all closed orders (with or without differences) to be successful and the variable “Result of processing a request” will have a value of 1, otherwise it will be 0. The rate of the successfully closed orders is a quite high in the sample – 95.29%.

– The commercial performance of the staff’s work in a pharma store can be associated with the relation of ordered and sold products. In case the client bought more than ordered, it can be considered the professional activity of the staff of a pharma store. In practice, this interpretation is not as clear as it seems. For example, the client should pay more than was declared in the marketplace just because of technical mistakes in the marketplace database or because the price was changed. But we assume that if the customer left more money in a pharma store, it can be positively evaluated by the owners of this business. This variable was named “Commercial performance” and can have a value of 1 if a difference is beneficial for the pharma store, otherwise it is 0 if a pharma store lost a part of the ordered amount or value of ordered goods is the same as sold one.

– According to our previous assumption, it is quite logical to introduce a rate of fulfilling orders as a variable "Precise sales". It is also binary variable that can have a value of 1 when an order was filled without any differences, and 0 otherwise.

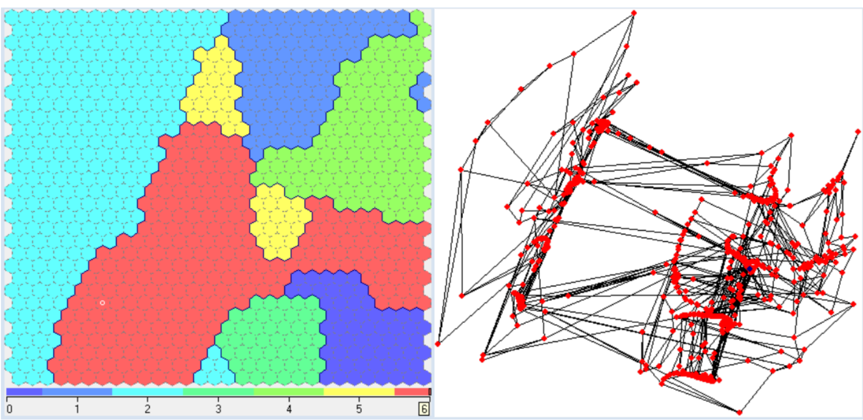
The general descriptive statistics can be found in Fig. 1, which provides an overview of our research sample. Basically, it demonstrates high variations inside, that is normal considering raw data extraction from the statistics of the marketplace.

Variable	Obs	Mean	Std. Dev.	Min	Max
ValueRrequ~d	3,672	294.3328	385.4414	4.8	4527
ValueSold	3,672	286.7092	378.6401	0	4074.3
ExtraSales	3,672	-7.623638	74.13246	-1833	337.9
Processing~t	3,672	.9528867	.21191	0	1
ComPerform~e	3,672	.0073529	.0854451	0	1
Precisesales	3,672	.875817	.3298351	0	1
TimeRespon~S	3,672	1551.268	6479.779	1	55131

Fig. 1. Descriptive statistics of the main variables in the dataset

Accumulated a significant number of the observations in our research sample, we can start with clustering and deriving a set of homogeneous groups of objects to identify patterns inherent in them. As shown in [4, 18, 19], Kohonen self-organizing maps have a number of advantages over other clustering methods. In particular, in addition to the ability of efficient processing large data sets, the location of the objects under study on the map allows to determine how developed the feature under study is compared to others, since the best and worst objects for this feature are located in opposite corners of the SOM. The defined clusters will be subjected to statistical analysis and on their basis it will be possible to build neural networks for predicting the values of target indicators, developing practical recommendations at the end.

In Deductor Studio, we created SOM with the following specifications: it contains 900 neurons; number of training epochs is 1000; SOM was initialized based on the internal vectors, and Gaussian with an initial learning radius of 8.5 was used as the neighbourhood function. As a result of conducting numerous experiments, from the general database of indicators it was selected a set of 5 most significant features, which provided the most adequate division of observations into clusters: "Value of request", "Time of response", "Precise sales", "Commercial performance", and "Result of processing a request". The derived 7 SOM clusters are shown in Fig. 2 together with the Sammon projection.



(a) (b)

Fig. 2. Clusters (a) and Sammon projection (b) of SOM

Based on the Fig. 2.b it is easily to notice that the Sammon projection indicates two groups of clusters constructed by the developed SOM. According to our approach described at the beginning of the study, these two groups may lead us to at least two commercial policy.

The heat maps of each of the selected indicators on the developed Kohonen map are presented in Fig. 3. These heat maps allow us to analyse the distribution of values across clusters for each of the purchase characteristics used in the research.

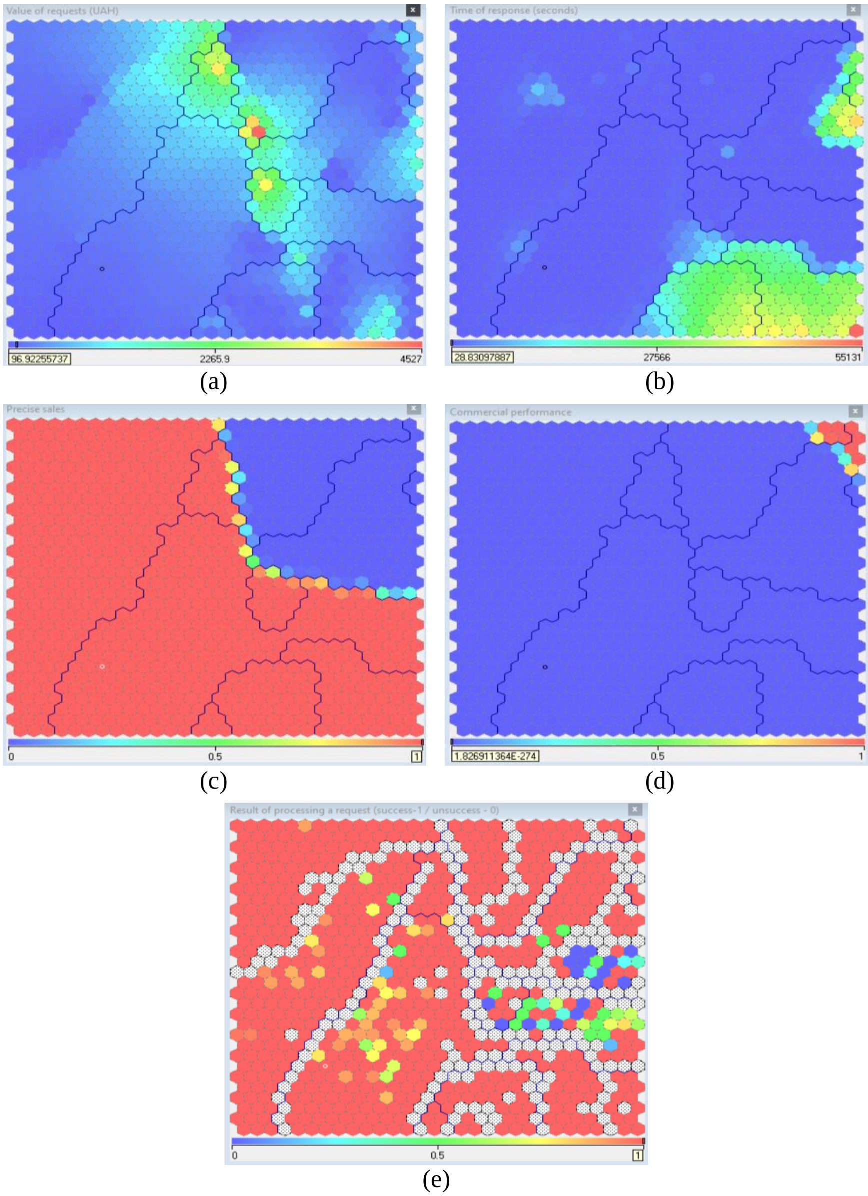


Fig. 3. Heat maps for chosen indicators

Observing information on the heat maps we would like to point to the upper-right corner of all figures. Neurons of this corner belong to 2 clusters (clusters 1 and 4, numbered in the colour line below the map in Fig. 2.a) and they indicate the high level of commercial performance (see Fig. 3.d) inside the set of sales with differences from orders (since the indicator "Precise sales" has a low value for all the neurons in these clusters, which can be seen in Fig. 3.c, this indicates that almost all purchases here were below the order value, except for the top right corner – see Fig. 3.d), with the cost of requested pharmaceutical goods below the average (see Fig. 3.a). These neurons are interested due to the fact that there are a small number of cases when customers do not buy anything (in cluster 4, as can be judged from Fig. 3.e in combination with Fig. 3.c), but in a number of cases the store personnel had worked better and finally motivated them to buy goods for a large amount. The detached area in the lower-right corner included neurons also from two clusters (0 and 3, which can be seen in Fig. 2.a) that have longer response time (see Fig. 3.b) with the successfully sold products (Figs. 3.c, 3.d).

As can be seen from Fig. 3.a, the majority of all orders via the marketplace for all clusters were made for small amounts – about 200 UAH. Requests around 4000 - 4500 UAH are really quite rare. In the centre of heat map in Fig. 3.a is located a group of neurons, with cluster 5 at its core, with higher prices of requested goods. This structure can provide information about the behaviour of consumers and pharmacy operators, and the purchasing prices in online pharma retail. The heat map in Fig. 3.b describes that the pharma stores respond quickly to orders that hit these neurons, but Fig. 3.c indicates that expensive orders are located very close to the border between clusters, when our indicative variable "Precise sales" changes its value from sales without differences from the order to changed ones. It should be also noticed that the price of the check in pharmacies for expensive orders did not increase, which can be seen from the map in Fig. 3.d, while all such sales were successfully completed, which can be judged from the map in Fig. 3.e.

Let's present in Fig. 4 the differences in the time responses of pharma stores in the sample.

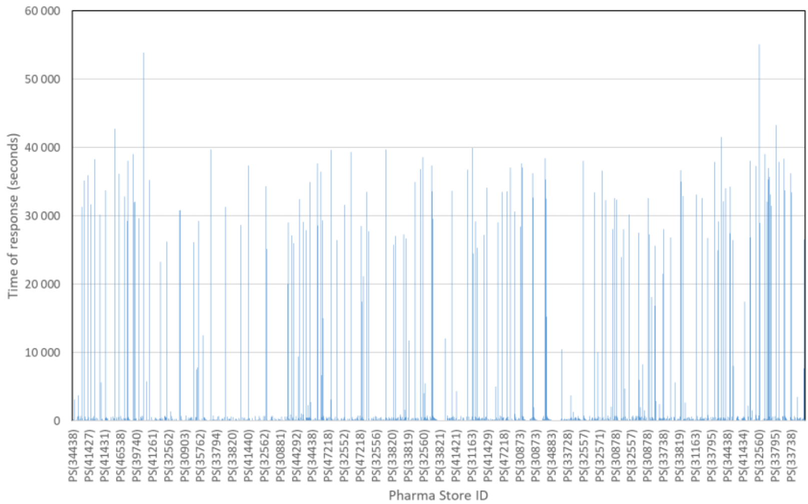


Fig. 4. Time of a pharma store's response after receiving a customer order via the marketplace

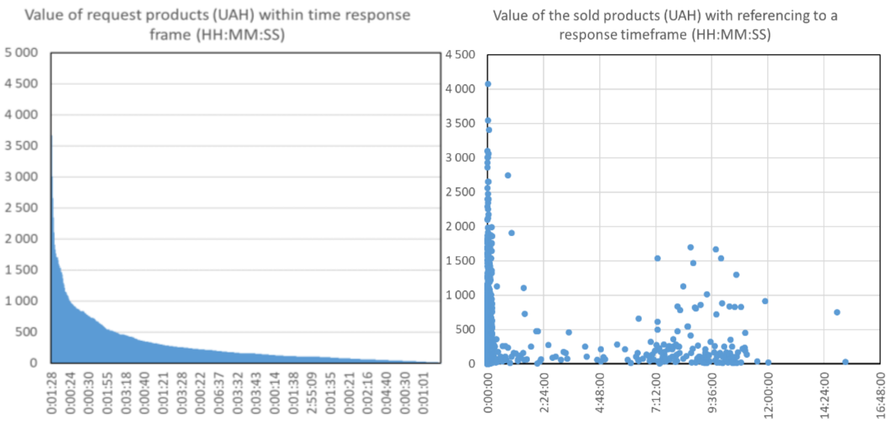
The diagram in Fig. 4 obviously is not able to present all pharma stores but we have to notice significant differences in this indicator for different pharma stores in the sample. The standard deviation of this indicator, as can be seen from Fig. 1, is 6479.78 seconds in response (or 1.8 hours). If you look closer at the diagram, you will notice that the majority of the responses are quite fast, which allowed to achieve an average response time for the entire sample of 25.85 minutes. According to order-placement procedure after the filling online form on the marketplace website, the staff of the selected by the customer pharma store should confirm this order and inform the client about time of reservation and availability of requested products. There are various approaches in the pharma stores to manage this order-placement process:

– Requests are processed by the responsible pharma store employee, who is in front of the laptop screen and performs all steps as fast as possible.

– All employees in the pharma store are involved in processing requests. It means that a person who is free at the moment will be able to send response to the marketplace request.

– Responsibility for managing these requests is on the seller at the cash desk who has to sell products for all clients in the pharma store and can answer on the marketplace request when he/she has time.

All above-mentioned approaches have advantages and disadvantages, but this variety leads to differentiation in the sample, which probably determines some patterns in the behaviour of employees and clients. We prepared two diagrams to clarify this issue (see Fig. 5).



(a) (b)

Fig. 5. Values of requested (a) and sold (b) products via the marketplace referencing to the time of responses in pharma stores in the sample

The presented in Fig. 5 diagrams allow us to conclude about existing some relationship between values of ordered or sold products and the time of response in the sample. The diagram in Fig. 5.b indicates that we may have two types of order processing by staff of pharma stores:

– With the first type, the order is processed quickly. Probably, this primarily concerns the first approach to managing the order-placement process, when orders are processed by a specially appointed person. Also, as can be seen in Fig. 5.a, the higher the cost of the order, the faster it is processed. This indicates that with any type of order-placement process, information systems notify about the order amount so as not to miss a profitable client. As can be seen in Fig. 3.b, clusters 2, 5, 6 and partially 1 correspond to such types of order processing.

– The second type of order processing generally takes between 6 and 11 hours, as can be seen in Fig. 5.b. Such a protracted response to a request may be due to the specificity of the order and its search in warehouses, as well as the approach used to manage the order-placement process, when there is no person responsible for processing requests. As already mentioned, clusters 0 and 3, and partially 1 and 4, correspond to long-term order processing, as can be seen in Fig. 3.b.

As we mentioned before, the values of ordered and sold products have quite a high correspondence with a difference of 12.45%. Moreover, all the differences between sales and orders are concentrated in clusters 1 and 4 of SOM, as can be seen in Fig. 3.d, and unsuccessful order processing is concentrated in the central right part of the map in clusters 4 and 6, as seen in Fig. 3.e. In this regard, we can observe that consumers more often don't take requested products away from the pharma stores than they buy additional goods after order placement (see Figs. 1 and 6).

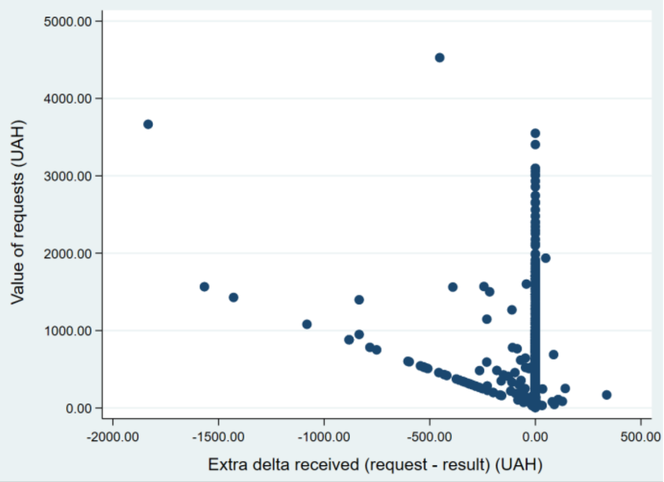


Fig. 6. Distribution of extra sales and value of ordered products in the pharma stores

The diagram in Fig. 6 shows that the majority of clients buy only requested products via the marketplace (this is marked by points with zero Extra delta received value on the x-axis). These are all the clusters of the Kohonen map except 1 and 4, as can be seen in Fig. 3.c. The points along the inclined line on the left side of the figure indicate a complete order rejection (for them, Extra delta received, marked on the x-axis, equals Value of requests on the y-axis, which resets the order). The points above this line symbolize a partial decrease in the order cost. This left part of Fig. 6 corresponds to the large parts of clusters 1 and 4, highlighted in blue in Figs. 3.c and 3.d. And the red part in Fig. 3.d corresponds to the right part of Fig. 6 and indicates additional sales in the pharmacy compared to the order through the marketplace.

We already have mentioned above the close correlation between requested and sold pharma products in the sample and the QQ plot in Fig. 7 confirms this fact.

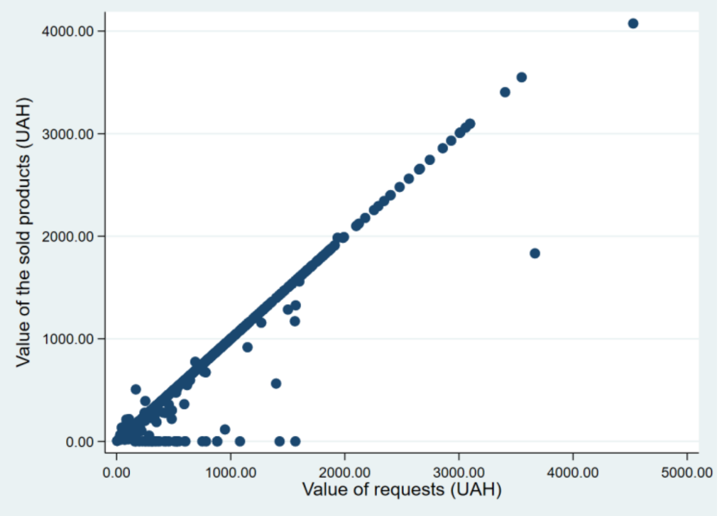


Fig. 7. Plot of values of requested and sold products in the pharma stores

Considering the resultative indicator of the commercial activity of pharma stores on the market place and taking into account outcomes of the previous statistical estimations, we will use the value of sold products as a final analytical construct. All other variables in the data set will support increasing the level of this indicator as a final result of an each commercial operation in a pharma store. Given the large sample size, when choosing mathematical tools, preference was given to perceptron-type neural networks, since they are much more effective on big datasets in comparison with econometric models [20, 21]. Fig. 8 shows a neural network developed in the Deductor Studio, which was trained using the "Resilient Propagation" algorithm.

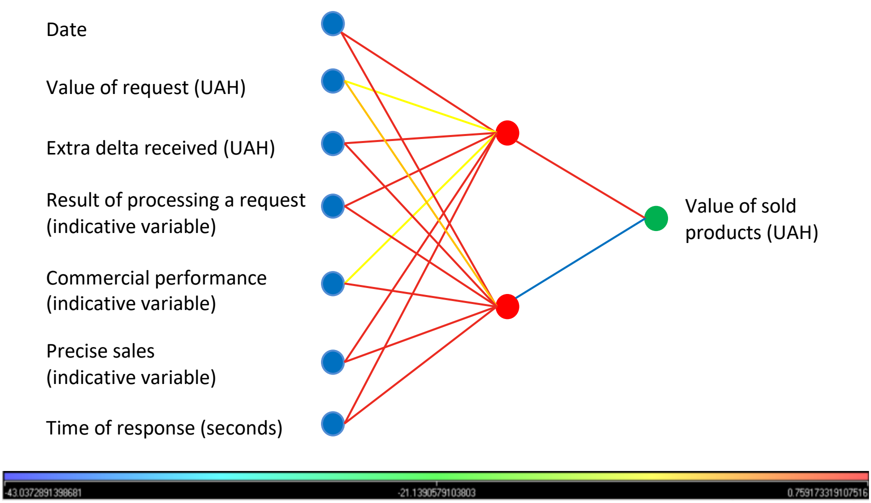
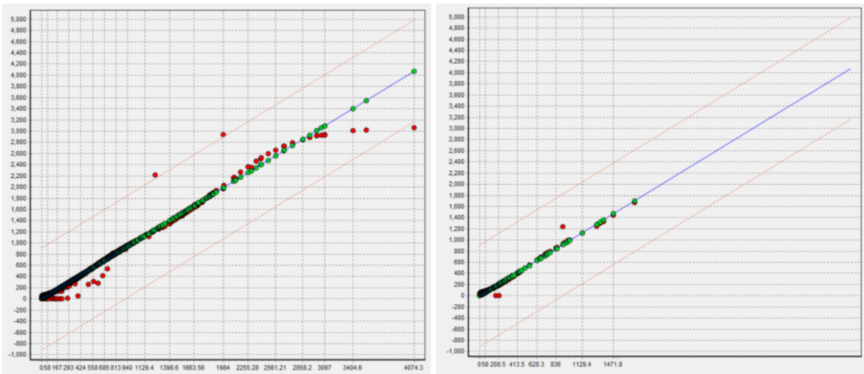


Fig. 8. The neural network for predicting the value of sold products

The level of connection strength between neurons of perceptron in Fig. 8 is indicated by the colour. For assessing the accuracy of the forecasting results based on the developed neural network, we present in Fig. 9 the scatter diagram, which allows us to evaluate the quality of the model by comparing the real values of the output variable and those predicted by the model (while monitoring whether the actual values are within the forecast confidence interval).



(a) (b)

Fig. 9. The scatter diagram of the developed forecasting neural network for training (a) and test (b) samples

Generally, the scatter diagram in Fig. 9 allows us to conclude that the prices of sold products and the values of the same indicator predicted by the model almost completely coincide and are inside the confidence interval. The close settlement of estimated values to the diagonal landmark (ideal values) show that the errors of our neural network are quite small (here green points – actual prices of sold products; red points – prices of sold products estimated by perceptron; red lines – confidence intervals with an error probability of up to 0.05; the blue line – the line of ideal values). As can be seen from the scatter diagrams, the forecast on the test sample (Fig. 9.b) turned out to be even more accurate than on the training set (Fig. 9.a). This testing diagram indicates quite accurate results of our neuro-net simulation that can be used for forecasting, decision-making or other purposes.

Conclusions

Digitization of economic subsystems and the intensive development of omnichannel commerce are among the most powerful drivers of economic growth. The progress of technology and the improvement of pharmaceutical industry distribution channels are a priority of the state policy in most countries to enhance the welfare and quality of life of the population.

To identify promising directions and levers for increasing the efficiency of Ukrainian pharmaceutical online retail enterprises, the authors of the article used a set of neural network and statistical analytical tools, which have been tested on a dataset of over a hundred pharmacy stores.

First of all, it was carried out clustering using the Kohonen self-organizing maps tool, which made it possible to identify patterns in the behaviour of customers and pharmacy staff in the process of fulfilling orders for pharmaceutical products. A study of the clustering results, supported by statistical analysis, showed that the speed of request execution is always high when the order price is high. In other cases, the order will most likely be processed either within a couple of hours or within 6 to 11 hours. And the article explains that this will depend on the order-placement procedure (how the order processing is set up in each individual pharmacy).

A neural network model of the perceptron type was also built to predict the value of sold products as the final result of each commercial operation in the pharmacy. Evaluation of the accuracy of forecasting results based on the developed neural network model using a scatter diagram confirmed its high efficiency.

As a further development of this study, we envision optimizing the actions of pharmacy staff in the process of performing the order-placement procedure in terms of processing orders and the work of staff to increase the purchase receipt, which should lead to increased productivity of the pharmaceutical business.

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