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PREDICTION OF LONG-TERM TREATMENT IN PATIENTS WITH COVID-19 BASED ON ANALYSIS OF THEIR PRIMARY EXAMINATION DATA

ABSTRACT

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Introduction. The COVID-19 pandemic has caused enormous social and economic damage. A significant part of people who have contracted this infection have serious health problems. To prevent the long-term consequences of COVID-19, models for predicting the duration of treatment based on prognostic factors obtained at the beginning of the disease are needed.

Materials and Methods. In 2020-2021, a survey of 832 patients with COVID-19 was conducted. With the help of computer programs Microsoft Excel 2021 and Statistica 12.0 Trial Version for Windows, the collected database was processed. The relationship between numerical predictors was investigated using Spearman's correlation, and between categorical indicators – gamma correlation. To predict the duration of the patient's treatment based on the initial clinical symptoms and signs, the tools of the Statistica 12.0 program "classification trees" were used. The model was built using the tool Data Mining – Trees/Partitioning – C&RT (Classification and Regression Tree).

Results and Discussion. During the study period, it was established that the long-term treatment of patients with COVID-19 depends on age, concomitant diseases, shortness of breath, body temperature, chest pain, frequency of respiratory movements in 1 minute, pain in the heart area, average blood pressure and heart rate according to 1 minute. This is confirmed by a significant difference between the groups of patients who were treated for up to 30 days and 31 days and more, as well as established correlations. On the basis of the above-mentioned predictors, a decision-making algorithm was developed to determine the duration of patient treatment.

Conclusions. Established interrelationships between clinical symptoms in patients with COVID-19 will allow timely detection of possible complications in patients. Implementation of a built decision-making model based on leading predictors will help doctors predict the duration of the infection and develop effective measures to prevent serious post-infection consequences.

Keywords: questionnaires, COVID-19, risk groups, clinical symptoms and signs, prognosis.

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ПРОГНОЗ ДОВГОТРИВАЛОГО ЛІКУВАННЯ ХВОРИХ НА COVID-19 НА ПІДСТАВІ АНАЛІЗУ ДАНИХ ЇХ ПЕРВИННОГО ОБСТЕЖЕННЯ

Вступ. Пандемія COVID-19 завдала колосальних соціальних та економічних збитків. Значна частина осіб, які перехворіли на цю інфекцію, мають серйозні порушення у стані здоров'я. Для запобігання віддалених наслідків COVID-19 необхідні моделі прогнозування тривалості лікування на підставі клінічних ознак, отриманих на початку захворювання.

Матеріали та методи. У 2020-2021 роках проведено опитування 832 хворих на COVID-19. За допомогою комп'ютерних програм Microsoft Excel 2021 та Statistica 12.0 Trial Version для Windows проведено опрацювання зібраної бази даних. Зв'язок між числовими предикторами досліджували за допомогою кореляції Спірмена, а між категорійними показниками – гамма-кореляції. Для передбачення тривалості лікування пацієнта на підставі початкових клінічних ознак застосовані інструменти програми Statistica 12.0 «класифікаційні дерева». Побудовано модель за допомогою засобу Data Mining – Trees/Partitioning – C&RT (Classification and Regression Tree).

Результати та обговорення. На період дослідження встановлено, що довготривале лікування хворих на COVID-19 залежить від віку, супутніх захворювань, задишки, температури тіла, болю у грудній клітці, частоти дихальних рухів за 1 хвилину, болю в області серця, середнього артеріального тиску та частоти серцевих скорочень за 1 хвилину. Це підтверджено суттєвою різницею між групами пацієнтів, які лікувалися до 30 днів та 31 день і більше, а також встановленими кореляційними зв'язками. На підставі вищезазначених предикторів розроблено алгоритм прийняття рішень щодо визначення тривалості лікування пацієнтів.

Висновки. Встановлені взаємозв'язки між клінічними симптомами у хворих на COVID-19 дозволять своєчасно виявляти можливі ускладнення у пацієнтів. Впровадження побудованої моделі прийняття рішень на підставі провідних предикторів допоможе лікарям прогнозувати тривалість перебігу інфекції та розробляти ефективні заходи для попередження серйозних постковідних наслідків.

Ключові слова: анкети, COVID-19, групи ризику, клінічні симптоми та ознаки, предиктори, прогноз.

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INTRODUCTION / ВСТУП

The pandemic of the coronavirus disease 2019 (COVID-19) has caused enormous social and economic damage [1]. According to official WHO statements, it lasted from March 11, 2020, to May 5, 2023. In Ukraine, the first cases of COVID-19, including fatal ones, began to be registered in March 2020; on July 1, 2023, the Ministry of Health of Ukraine also announced the end of the pandemic and the cessation of strict quarantine measures. During this period, more than 2 million people died in the European region [2], while in Ukraine – 112,418 people died; the mortality rate was 2.0% [3], while among hospitalized patients, this value reached 9.6–11.6% [4]. Approximately 15% of patients had a severe course of COVID-19; respiratory and cardiovascular complications with manifestations of acute respiratory distress syndrome, thromboembolism, and septic shock occurred in 5% of patients [5].

The introduction of restrictive measures, including strict quarantine [6], social distancing [7], the use of personal protective equipment, etc. [8] somewhat stopped the spread of the COVID-19 pathogen. At the same time, the specific prophylaxis affected the severity of the coronavirus infection [9]. In addition, in the process of adapting to the human population as its biological host, the virus began to gradually reduce virulence, but increase susceptibility to it due to the evolution of the protective antigen towards affinity with human cell receptors. At the same time, measures aimed at preventing COVID-19, the massive use of expensive diagnostic tests, and the long-term treatment of patients altogether caused significant economic losses [10].

During the COVID-19 pandemic, the formation of a new parasitic system continued, accompanied by further genetic and antigenic changes in the SARS-CoV-2 virus and the emergence of new variants (Alpha, Beta, Gamma, Delta, and Omega) with a wide range of mutations, which allowed evading specific antibodies acquired through previous infection or vaccination [11, 12]. This led to the risk of recurrent diseases within a short period, reducing the effectiveness of treatment and specific prophylaxis [13, 14]. It became impossible to predict the development of the infectious process based on the levels of specific antibodies determined at the beginning of the disease [15]; that is, this indicator lost its relevance in characterizing the degree of a person's protection against this infection.

In the post-pandemic period of COVID-19, which is still accompanied by constant mutation of SARS-CoV-2 [16], probable seasonal epidemic outbreaks [17, 18], and an increase in morbidity among children [19], it is still relevant to solve the problem of reducing the burden of the disease on the healthcare system and personalizing its treatment by optimization of approaches to medical care provision to patients with COVID-19.

In patients with COVID-19, the course was characterized by a complex of clinical symptoms with an acute period (sometimes lasting for 4 weeks) and a prolonged recovery of more than 2 months [20]. The most common initial clinical symptoms were headache, fatigue, myalgia, sore throat, and cough; arthralgia, fever, chills, rhinitis, nausea, conjunctivitis, and dizziness were also considered common symptoms [21, 22]. The main post-COVID clinical symptoms are fatigue, muscle or joint pain, shortness of breath, and sleep disturbances; additional symptoms include depression and anxiety, loss of smell and taste, headache, and "brain fog" [23, 24]. All of these COVID-19 symptoms have a significant negative impact on the patient's quality of life. Therefore, to prevent the long-term consequences of COVID-19, the search is currently ongoing for the signs that can help assess disease severity and long-COVID risks, taking into account the duration of recovery.

Given the above, the work aimed to construct a model for long-term treatment prognosis in COVID-19 patients, which suggests an algorithm for predicting the duration of treatment and long-COVID risks in patients based on data analysis from their initial examination.

MATERIALS AND METHODS

In Kharkiv, during 2020-2021, 832 adult patients with COVID-19 were surveyed upon initial visit to a doctor; 492 questionnaires were filled out for outpatients, and 331 questionnaires were filled out for inpatients. The questionnaires contained the patient's passport data and social status (age, gender, place of work), disease history (dates of disease onset, visits to a doctor, duration of treatment), clinical and diagnostic aspects (laboratory tests, concomitant diseases, clinical symptoms, complications), and epidemiological data (source of the infectious agent, place of infection). The study was based on the hypothesis that the initial clinical symptoms and laboratory findings in COVID-19 patients can help predict their treatment duration and long-COVID risks.

Statistical analysis of the collected data was carried out using the computer programs: Microsoft Excel 2021 and Statistica 12.0 Trial Version for Windows. The following methods were used: statistical grouping and analysis of pivot tables, the chi-squared test (for identifying a significant difference between groups), nonparametric analysis of variance, and multiple comparisons of group mean values. The association between numerical predictors was examined using Spearman's rank correlation, and between categorical data – using gamma correlation.

To predict the duration of a patient's treatment based on the signs recorded during the initial examination, the tools of the Statistica 12.0 program ("classification trees") were used. The model was built using the Data Mining – Trees/Partitioning – C&RT (Classification and Regression Tree) tool; the number of nodes was 15, and the overall classification accuracy was 0.696233 [25, 26].

According to our observations and literature data [20], in the first years of the pandemic, the acute period in patients with COVID-19 lasted up to 4 weeks, which allowed us to conditionally divide patients into two groups according to the duration of the infection: Group 1 – duration of treatment up to 30 days; Group 2 – duration of treatment ≥ 31 days. The target or dependent variable was long-term treatment (a binary variable that was equal to 0 if the duration of treatment was up to 30 days and equal to 1 if the duration of treatment was 31 days or more). The input data were dominated by records with treatment durations of up to 30 days in a ratio of 7:1.

Predictors, or independent variables, were age, respiratory rate (RR), saturation (SpO2%), heart rate (HR), mean blood pressure (BP), body temperature, chills, dyspnea, nasal congestion, rhinitis, dry mouth, chest pain, chest heaviness, shortness of breath, pain in the heart area, palpitations.

Using a "classification tree" or "decision tree," we made an algorithm to predict the target indicator based on input data.

The classification quality is characterized by two main characteristics – classification accuracy and classification error, and depends on the configuration of the classification tree construction procedure – method options and stopping options. Classification accuracy is calculated as the ratio of correctly classified objects using the generated rules to the total number of objects in the dataset. The classification error rate is calculated as the ratio of objects incorrectly classified using the formed rules to the total number of objects in the dataset.

The most accurate prediction is considered to be the one associated with the lowest percentage of misclassified observations.

RESULTS

At the beginning of the work, the duration of treatment of 823 COVID-19 patients was divided into the following periods: up to 14 days, 15 to 30 days, 31 to 45 days, ≥ 46 days. It was shown that the distribution of outpatients and inpatients (492 and 331 patients, respectively) by these terms had similar values. However, the majority of outpatients (67.89%) and inpatients (69.49%) were treated for 15 to 30 days (Table 1).

Table 1 – Distribution of outpatients and inpatients with COVID-19 by duration of treatment

Recovery period	Outpatients		Inpatients		Total	
	Absolute number	%	Absolute number	%	Absolute number	%
Up to 14 days	92	18.70	63	19.03	155	18.83
15 to 30 days	334	67.89	230	69.49	564	68.53
31 to 45 days	56	11.38	32	9.67	88	10.69
≥ 46 days	10	2.03	6	1.81	16	1.94
Total	492	100.00	331	100.00	823	100.00

When determining risk groups by age and health status, we found that the proportion of outpatients over 65 (18.5%) was almost 2 times lower than that of inpatients of this age group (36.86%). In the structure of inpatients, 82.78% of people had concomitant diseases, while among outpatients, this group included almost 2.5 times less subjects (28.46%).

A significant proportion of patients from the age risk group (over 65 years) and other age groups were treated for 15 to 30 days (68.54% and 68.52%, respectively), but a significant difference was found between these groups with regard to the treatment for more than 30 days (21.13% versus 9.68%), ($p<0.001$). Individuals from the health condition risk group and individuals who did not belong to this group were also mainly treated for 15–30 days (68.53% and 68.12%, respectively); however, individuals from the risk group almost 3 times more often received treatment for more than 30 days (18.6% versus 6.6%) (Table 2).

To establish the leading prognostic factors (predictors) that characterized the clinical course of COVID-19, patients were divided into 2 groups according to the duration of treatment: Group 1 – treatment period of up to 30 days (719 people – 87.36%) and Group 2 – treatment period of ≥ 31 days (104 people – 12.64%). The probability of treatment duration of up to 30 days was 0.8736 (ratio 719:823), and of ≥ 31 days was 0.1264 (ratio 104:823). The distribution of treatment duration was approximately the same in women and men ($p=0.2982$) and in outpatients and inpatients ($p=0.4128$), except for age groups. The treatment period for elderly people was significantly longer ($p=0.000008$).

Table 2 – Distribution of COVID-19 patients from risk groups by age and health status depending on the duration of treatment

Recovery period	Age groups (%)			Health status (%)		
	Others	Risk group	Total	Others	Risk group	Total
Up to 14 days	21.80	10.33	18.83	24.45	13.29	18.83
15 to 30 days	68.52	68.54	68.53	68.95	68.12	68.53
≥ 31 days	9.68	21.13	12.63	6.6	18.6	12.63
Total	100.00	100.00	100.00	100.00	100.00	100.00

Most patients, upon initial visit to a doctor, reported the following clinical symptoms: weakness (95.99%), cough (88.82%), headache (81.65%), chills (72.3%), muscle pain (65.49%), dyspnea (60.27%), sleep disturbances (55.53%), shortness of breath (52.13%), chest heaviness (51.76%).

In both groups of COVID-19 patients, 22 clinical symptoms were recorded; for 10 symptoms of these, we found a significant difference between the proportions of individuals in these groups. Thus, in Group 1, most patients reported dry mouth, pain in the chest and heart area, while patients in Group 2 experienced chills, dyspnea, nasal congestion, rhinitis, heaviness in the chest, shortness of breath, and palpitations (Table 3).

Table 3 – Distribution of COVID-19 patients by clinical symptoms depending on the duration of treatment

Symptoms	Group 1 (%)	Group 2 (%)	p
Chills	71.07	80.77	$p = 0.038$
Dyspnea	56.61	85.58	$p = 0.0001$
Nasal congestion	59.53	72.12	$p = 0.013$
Rhinitis	68.85	78.85	$p = 0.037$
Dry mouth	69.26	58.65	$p = 0.030$
Chest pain	75.94	54.81	$p = 0.0001$
Chest heaviness	50.07	63.46	$p = 0.01$
Shortness of breath	50.63	71.15	$p = 0.0001$
Pain in the heart area	87.62	69.23	$p = 0.0001$
Palpitations	57.3	60.58	$p = 0.0006$

Almost equally, COVID-19 patients from different study groups reported weakness, cough, headache, anosmia, ageusia, sore throat, muscle pain, nausea, vomiting once a day, diarrhea once a day, abdominal pain, and sleep disturbances.

Comparison of the proportion of clinical signs (age, respiratory rate, SpO2%, heart rate, mean blood pressure, body temperature) in COVID-19 patients revealed a significant difference between groups (Table 4).

Table 4 – Distribution of COVID-19 patients by clinical signs depending on the duration of treatment

Signs	Group 1 (мean)	Group 2 (мean)	p
Age, years	53.3	60.7	$p = 0.0001$
SpO_2 %	94.4	92.7	$p = 0.001$
Heart rate	86.7	91.0	$p = 0.001$
BP, mm Hg	95.1	98.1	$p = 0.0005$
Respiratory rate	20	21.2	$p = 0.0001$
Body temperature (°C)	37.7	37.9	$p = 0.002$

We revealed a weak relationship in most cases by investigating the correlation for age, respiratory rate, SpO2%, heart rate, blood pressure, and body temperature. At the same time, a direct relationship was observed between age and mean BP, between age and respiratory rate, and an inverse relationship was observed between age and SpO2% and between respiratory rate and SpO2%. The strength of these relationships differed somewhat across groups (Table 5).

Table 5 – Correlation analysis of clinical signs in COVID-19 patients depending on the duration of treatment

Group 1

Signs	Treatment duration up to 30 days Spearman rank order correlations (marked correlations are significant at $p < 0.05000$)					
	Age	Respiratory rate	SpO_2 %	Heart rate	Mean BP	Body temperature
Age	-	0.234619	-0.336552	-0.027046	0.393047	-0.055903
Respiratory rate	0.234619	-	-0.430227	0.141372	0.143938	0.038284
SpO_2 %	-0.336552	-0.430227	-	-0.247227	-0.206146	-0.207534
Heart rate	-0.027046	0.141372	-0.247227	-	0.116405	0.199022
Mean BP	0.393047	0.143938	-0.206146	0.116405	-	0.044951
Body temperature	-0.055903	0.038284	-0.207534	0.199022	0.044951	-

Group 2

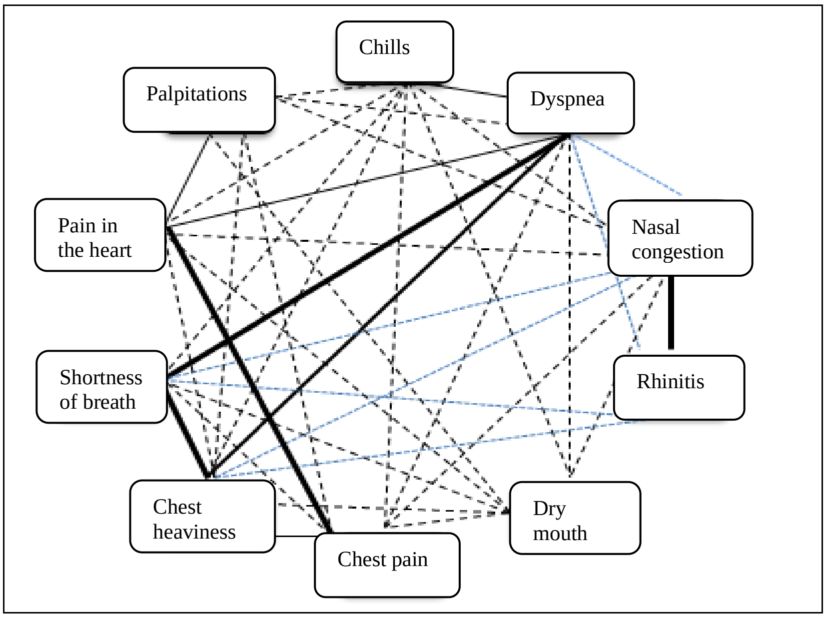
Signs	Treatment duration ≥31 days Spearman rank order correlations (marked correlations are significant at $p < 0.05000$)					
	Age	Respiratory rate	SpO_2 %	Heart rate	Mean BP	Body temperature
Age	-	0.015310	-0.185683	0.117567	0.379115	-0.027094
Respiratory rate	0.015310	-	-0.222187	0.334264	-0.094254	0.013746
SpO_2, %	-0.185683	-0.222187	-	-0.183170	-0.177230	-0.201117
Heart rate	0.117567	0.334264	-0.183170	-	0.023795	0.217145
Mean BP	0.379115	-0.094254	-0.177230	0.023795	-	0.214702
Body temperature	-0.027094	0.013746	-0.201117	0.217145	0.214702	-

At the same time, direct strong correlations were established between clinical symptoms. Thus, in Group 1, there was a correlation between shortness of breath and dyspnea, between dyspnea and heaviness in the chest, between shortness of breath and heaviness in the chest, between pain in the heart area and pain in the chest, while in Group 2, there was a correlation between dyspnea and pain in the heart area, between dyspnea and shortness of breath, between pain in the heart area and palpitations, between shortness of breath and heaviness in the chest (Fig. 1).

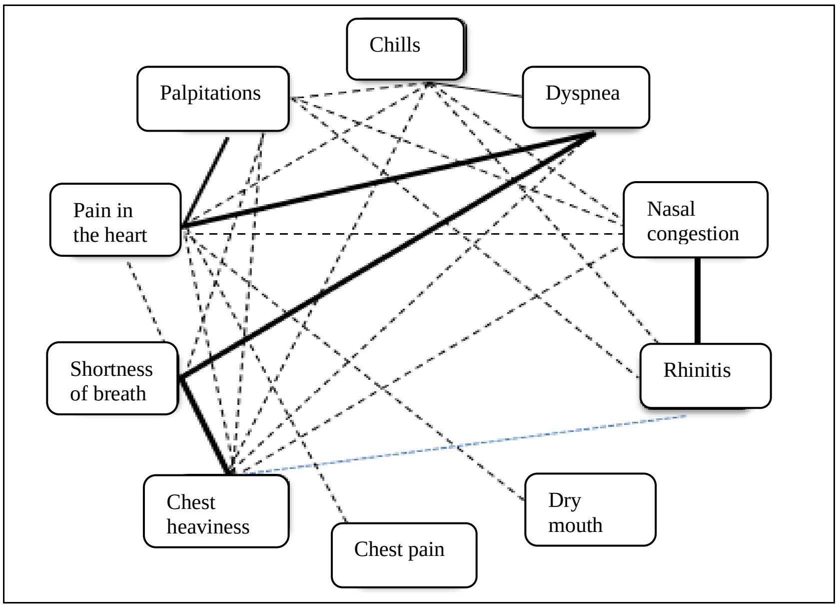
The established relationships between clinical symptoms, especially in Group 2, can be used as prognostic factors to predict long-term treatment and long-COVID development risks. In addition, correlation analysis confirmed the association between the clinical symptoms studied; it allowed us to include these symptoms in the classification tree model.

A classification tree is one of the prediction methods that can be used if there is a correlation between predictors. The basic idea is to create a model in the form of a "decision tree" that systematically examines data and makes decisions based on conditions learned from the data.

Therefore, to predict the duration of treatment based on predictors (clinical symptoms and signs in COVID-19 patients) identified during the initial examination of patients, we constructed a classification tree model (Fig. 2).



Group 1 (up to 30 days)



Group 2 (≥ 31 days)

Figure 1 – Correlation analysis of clinical symptoms in COVID-19 patients with regard to treatment duration

Note:

Correlation assessment		Positive	Negative
correlation < 0.5	weak		
0.5 <= correlation < 0.7	average		
0.7 <= correlation < = 1	strong		

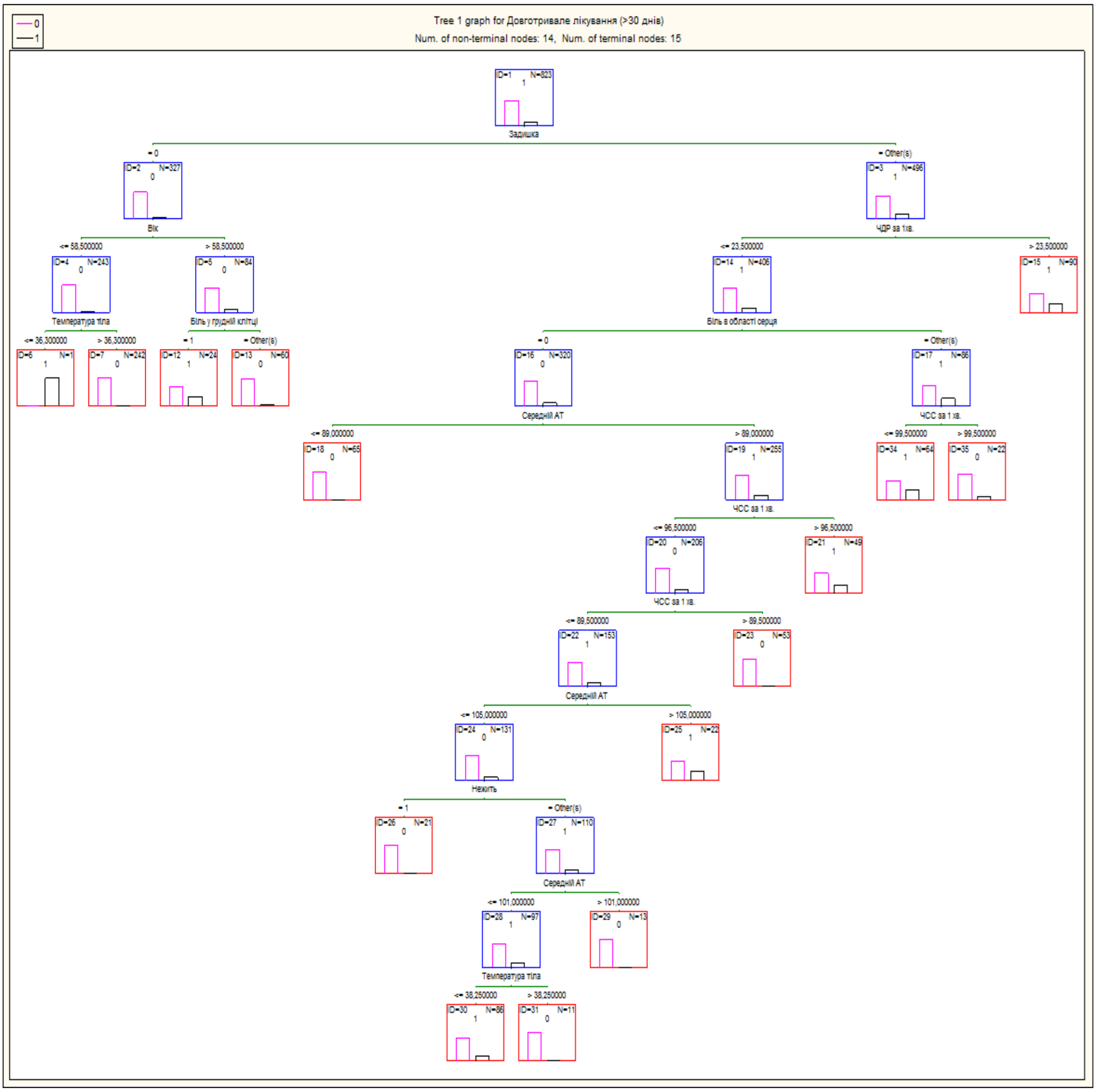


Figure 2 – A classification tree model with prognostic factors (predictors) identified in COVID-19 patients

Based on the constructed model, an algorithm was developed for decision-making with regard to the possible duration of treatment and the risk of developing long-COVID based on the predictors entered into the model. This algorithm involves a sequential assessment of certain patient characteristics to determine the need for long-term (31 days or more) or short-term (up to 30 days) treatment (Table 6).

DISCUSSION

Elderly and overweight people [27, 28], as well as people with diabetes, chronic respiratory and cardiovascular diseases, and other serious chronic diseases are at risk for COVID-19 [29, 30]. Therefore, it is likely that these individuals may require treatment for a long time and subsequently have serious long-term consequences after recovery. Among the 823 patients with COVID-19, 68.53% of patients were treated for 15–30 days, while 18.83% were treated for up to 14 days and 12.59% – for more than 30 days. Among those patients treated for more than 30 days, significantly more people were from risk groups by age and health status ($p<0.001$). Thus, there is an association between the severity and duration of COVID-19, age of ≥65 years, and a burdened premorbid background. At the same time, according to the results of our studies, no difference was found in the duration of treatment between women and men and between inpatients and outpatients, although the literature data reported a longer course of COVID-19 in women [31].

Table 6 – Algorithm for assessing the predicted duration of treatment

Steps	Actions
Step 1	Find out if the patient has dyspnea. If no, proceed to Step 2; if yes, proceed to Step 5
Step 2	If the age is ≤ 58.5 years, proceed to Step 3; if the age is > 58.5 years, proceed to Step 4
Step 3	If body temperature is ≤ 36.3 °C, then the treatment period is ≥ 31 days; otherwise the treatment period is up to 30 days
Step 4	Find out if the patient has chest pain. If yes, then the treatment period is ≥ 31 days; if no, the treatment period is up to 30 days
Step 5	Compare the patient's respiratory rate with the reference rate of 23.5 breaths per minute. If the respiratory rate is ≤ 23.5 breaths per minute, proceed to Step 6; otherwise, the treatment period is ≥ 31 days
Step 6	Find out if the patient has pain in the heart area. If no, proceed to Step 7; if yes, proceed to Step 14
Step 7	Compare the patient's mean blood pressure with the reference blood pressure of 89 mm Hg. If mean blood pressure is ≤ 89 mm Hg, then the treatment period is up to 30 days; otherwise, proceed to Step 8
Step 8	Compare the patient's heart rate with the reference rate of 96.5 beats per minute. If the heart rate is ≤ 96.5 beats per minute, proceed to Step 9; otherwise, the treatment period is ≥ 31 days
Step 9	Compare the patient's heart rate with the reference rate of 89.5 beats per minute. If the heart rate is ≤ 89.5 beats per minute, proceed to Step 10; otherwise, the treatment period is up to 30 days
Step 10	Compare the patient's mean blood pressure with the reference blood pressure of 105 mm Hg. If mean blood pressure is ≤ 105 mm Hg, proceed to Step 11; otherwise, the treatment period is ≥ 31 days
Step 11	Find out if the patient has rhinitis. If yes, then the treatment period is up to 30 days; otherwise, proceed to Step 12
Step 12	Compare the patient's mean blood pressure with the reference blood pressure of 101 mm Hg. If mean blood pressure is ≤ 101 mm Hg, proceed to Step 13; otherwise, the treatment period is up to 30 days
Step 13	Compare the patient's body temperature with the reference body temperature of 38.3 °C. If body temperature is ≤ 38.3 °C, then the treatment period is ≥ 31 days; otherwise the treatment period is up to 30 days
Step 14	Compare the patient's heart rate with the reference rate of 99.5 beats per minute. If the heart rate is ≤ 99.5 beats per minute, then the treatment period is ≥ 31 days; otherwise, the treatment period is up to 30 days

The patients with COVID-19 long-term course had more clinical symptoms, myalgia [32], tachycardia [33], and required antibiotics more often for their treatment [34]. Our analysis showed that a complex of symptoms, including chills, dyspnea, nasal congestion, rhinitis, dry mouth, chest pain, heaviness in the chest, shortness of breath, pain in the heart area, and palpitations (tachycardia), occurred in both groups of patients (Group 1 was treated for up to 30 days, Group 2 – for ≥ 31 days). However, in Group 2, their proportion was significantly higher, except for dry mouth, chest pain, and heart pain (these symptoms were more common in Group 1). The proportion of patients with clinical symptoms may vary depending on age group, immune system status, and other risk factors. It should also be noted that weakness, headache, anosmia, ageusia, sore throat, muscle pain (myalgia), nausea, diarrhea, and other symptoms were observed in patients in equal measure; at the same time, some of the symptoms could indicate pathological processes of the nervous system [35]. Therefore, the complex of symptoms that determine the severity of COVID-19, as well as tachycardia, may be risk factors for the long-term course of coronavirus infection [36].

Our studies have shown that the duration of COVID-19 can be estimated during the initial presentation of patients based on the analysis of clinical signs and symptoms such as age, respiratory rate, SpO2%, heart rate, mean blood pressure, body temperature, chills, dyspnea, chest pain, chest tightness, shortness of breath, and tachycardia. The data we obtained regarding the inverse relationships between age and SpO2% level, as well as between respiratory rate and SpO2%, are logical and do not require discussion. Different strengths of these relationships in groups with different treatment durations indicate that clinical parameters may change with increasing duration of disease or treatment. These data confirm important associations between clinical parameters in patients with COVID-19. Our findings also emphasize the need to consider the duration of the disease when analyzing these associations to better understand the course of the disease and develop optimal treatment regimens.

Therefore, correlation analysis between clinical symptoms may have important practical significance for clinical practice, which can help doctors to better understand the relationships between symptoms and identify possible complications in patients in a timely manner.

Some authors emphasize that short-term and long-term persistent effects after acute COVID-19 course have not been systematically assessed [35]. This makes it virtually impossible to predict the occurrence of post-COVID syndrome. In addition, the possible risk of antibody-dependent enhancement of COVID-19 should not be excluded in individuals who have been exposed to this infection or have been vaccinated against it and have specific antibodies with the theoretical potential to enhance infection or initiate immunopathy [37, 38].

Therefore, currently, prediction of long-term treatment in COVID-19 patients based on the analysis of the initial examination is necessary to develop effective measures aimed at preventing serious post-COVID consequences.

The constructed classification tree model based on prognostic factors (predictors) allowed us to define an algorithm, which is a type of decision tree based on sequential verification of certain clinical symptoms and signs to determine the duration of patient treatment. The main indicators used for the calculation include dyspnea, age, body temperature, chest pain, respiratory rate, pain in the heart area, mean blood pressure, and heart rate.

The main advantages of this algorithm are its simplicity and ease of interpretation. The algorithm is based on a sequential set of simple comparisons, making it easy to understand how decisions about treatment duration are made. In addition, it automates the decision-making process.

Thus, this algorithm could be a useful tool for automatic decision-making regarding the duration of patient treatment based on available clinical data.

CONCLUSIONS

1. It has been confirmed that advanced age and comorbidities are factors that can increase the duration of treatment in COVID-19 patients. Therefore, it is necessary to consider these patients as a risk group and prescribe antiviral therapy in a timely manner, as well as to carry out preventive measures during the pre-season increase in respiratory infection incidence.

2. The established relationships between clinical symptoms are of importance for clinical practice, as they help doctors better understand and monitor the condition of COVID-19 patients, identifying possible complications in a timely manner. In addition, confirmation of the correlation between predictors allowed us to construct a classification tree model for predicting the treatment duration based on clinical symptoms and signs identified during the initial examination of patients.

3. We are proposing an algorithm for predicting the treatment duration in patients with COVID-19 based on the analysis of the initial examination. The implementation of this model will help doctors predict the duration of the infection and implement measures to prevent serious post-COVID consequences.

4. Given the evolutionary changes of the SARS-CoV-2 virus and the reduction of the COVID-19 clinical course severity, it is necessary to continue work with regard to long-COVID risk prediction, in particular based on initial clinical symptoms.

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All authors substantively contributed to the drafting of the initial and revised versions of this paper. They take full responsibility for the integrity of all aspects of the work.

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CONFLICT OF INTEREST / КОНФЛІКТ ІНТЕРЕСІВ

The authors declare no conflict of interest.

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