Intelligent Analysis Impact of the COVID-19 Pandemic on Juvenile Drug Use and Proliferation

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Abstract

This paper examines the state of drug use and sales during a lockdown caused by a pandemic COVID-19. The focus group is juveniles in the United States, as there has been a sharp change in drug mortality for this group in the United States during quarantine. The change in the death rate from drugs among minors has been identified. The impact of drug prohibition and legalization in the US economy on the level of drug use has been studied. Data on drug use and distribution by juveniles were analyzed using descriptive statistics, data visualization, smoothing (Kendall, Pollard, median, exponential), data correlation, and cluster analysis. The results show that for minors aged 12-16, quarantine conditions have benefited by reducing the trend of drug use, not only after quarantine but also in later life, and confirm the hypothesis of a positive effect of lockdown on drug use reduction among minors in the United States. Recommendations are proposed to increase the attention of the state and its implementation of additional control measures, including conducting political and educational measures among adolescents to prevent drug use and reduce the popularity of drug use for each succeeding generation. It will positively benefit young people as drug prevention, and it will help reduce drug mortality in the United States.

Keywords

Statistical Analysis, Information Technology, Intelligent Analysis, COVID-19 Pandemic, Juvenile Drug Use, Juvenile Drug Proliferation, Business Analysis, Data Processing

1. Introduction

The problem of socio-economic development of each country, according to researchers [1-6], is very sensitive to changes in external influences [7-11], critical of which the last two years are the pandemic COVID-19 [12, 13]. During the pandemic in the United States, a record number of people died from drug overdoses, about 100 thousand Americans [14-16]. Mortality rates have increased by 35% compared to 2020. In 2019, the number of deaths due to drug exposure did not exceed 73 thousand. It is the largest number of overdose deaths registered in a year. According to the National Institute on Drug Abuse [15], this is the largest increase in drug overdose mortality since 1999 [17-19].

The fight against drugs has been going on for more than a century. The author [20] traces the history of drug use since the 19th century. In the 20th century, the cause of death from drug use was that drug addicts neglected treatment for a long time. It has been found that a large percentage of deaths are heroin users born from the 1990s to the 2000s during the baby boom [20-23]. During the baby boom, a generation was born that became a global drug user, and by 2022, the highest number of overdose deaths was recorded among drug addicts of this generation. Over 50 years, this has led to a sharp increase in drug use and frequency, as evidenced in all official documents and reports. From an economic point of view, it also led to the rapid growth of the drug business and its criminalization [14-16, 20-24]. The purpose of the work is as following.

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- Application of basic visualization methods, graphical display and primary statistical processing of numerical data on the impact of the COVID-19 pandemic on juvenile drug use and proliferation, presented by a sample.
- Study of trends in the behaviour of drug use by minors during the lockdown, using the basic methods of identifying trends in the behaviour of addictions that represent the nature of the trend of use,
- Presentation of the obtained results using MS Excel spreadsheet to confirm or refute the hypothesis of a positive effect of lockdown on reducing drug use among minors.
- Using methods of correlation analysis of experimental data to establish the relationship between copper data collected during the pandemic period.
- Application of the cluster analysis method to establish the cluster of the most drug-dependent age groups of minors.

The task is to study the impact of COVID-19 on the level of drug use by minors on the example of the largest data set on drug use in the United States. Identify the cluster of the most drug-dependent age groups of minors to develop ways to counteract the growth of drug use among young people.

2. Literature review

The problem of drug use by minors became acute after the Second World War. Several important documents have been adopted to control the spread of drugs. The Opium Convention was signed in 1909 in Shanghai [25]. It includes 13 countries of the International Opium Commission. It restricts exports as opposed to banning or criminalizing the use and cultivation of opium, coca and cannabis. The Convention provided that States would make every effort to control or seek to control all persons producing, importing, selling, distributing and exporting morphine, cocaine and their related salts, and buildings in which such persons are engaged in such industry or trade [25]. The Convention was replaced by the 1961 Single Convention on Narcotic Drugs. Ukraine was ratified by the Convention in 2001, but on the website of the Verkhovna Rada of Ukraine on December 2, 2020, the Commission on Narcotic Drugs decided to remove cannabis from List IV of the Convention after the proposals were published by the World Health Organization in 2019 [25].

However, today the problem is not solved in Ukraine or worldwide. New reports of increasing adolescent mortality from drug overdose are emerging [26-36]. During the quarantine of the COVID-19 pandemic, retailers adapted to new conditions [37-49]. Quarantine through COVID-19 increased unemployment and according to researchers [50-58], a certain part of the population was forced to look for means of survival that were quite easy to obtain.

Impact of quarantine on juvenile use [59-69]:

1. Forced isolation due to the difficult epidemiological situation with COVID-19 has affected young people differently.
2. Some have reduced consumption for reasons such as lack of parties and company, moving parents from the metropolis to the suburbs and provinces.
3. And others, on the contrary, began to use much more due to a large amount of free time; this category believes that buying drugs during the crown of the virus is safer than going to the supermarket.

Our work is based on data from research by the National Center for Health Statistics (NCHS), one of the leading statistical agencies under the US government [67]. It is located within several different organizations within the Ministry of Health and Social Services and, since 1987, has been part of the Centers for Disease Control and Prevention. They conduct four data collection programs: National Vital Statistics System (NVSS), National Health and Nutrition Examination Survey (NHANES), National Health Interview Survey (NHIS), and National Health Care Surveys (NHCS) [40-45].

The National Drug and Health Survey (NSDUH) is a significant source of statistics on illicit drug, alcohol, and tobacco use and on the mental health of US civilians over the age of 12 [46-58]. The survey tracks trends in specific interventions for substance use and mental illness and assesses the consequences of these conditions by examining and treating mental and substance use disorders [59-66, 68].

3. Methods

The following methods were used to solve the tasks [69-84].

- Data and information collection. Convert data to excel format.
- Descriptive statistics of data.
- Visualization (in polar and Cartesian coordinates; in the form of histograms, etc.).
- Smoothing according to Kendall formulas - a simple moving average, using the different intervals.
- Smoothing according to formulas from Pollard.
- Exponential smoothing, values of α = 0.1, 0.15, 0.2, 0.25, 0.3
- Median smoothing using the different intervals.
- Cluster data analysis.

4. Experiments and Results

4.1. Data

The work is based on data from the National Center for Health Statistics (NCHS) study, namely the NSDUH for 2020 [14, 40-41, 67]. The dataset consists of data on the frequency of drug use among ten age groups of minors in the United States from 12 to 21 years (Table 1). It covers 13 drugs across 10 age groups. The average value of the polled number of people is equal to 2671.

Table 1
US drug use by age dataset

n	age	alcohol	marijuana	cocaine	crack	heroin	hallucinogen	inhalant	pain-releiver	oxycontin	tranquilizer	stimulant	meth	sedative
2798	12	3,9	1,1	0,1	0,0	0,1	0,2	1,6	2,0	0,1	0,2	0,2	0,0	0,2
2757	13	8,5	3,4	0,1	0,0	0,0	0,6	2,5	2,4	0,1	0,3	0,3	0,1	0,1
2792	14	18,1	8,7	0,1	0,0	0,1	1,6	2,6	3,9	0,4	0,9	0,8	0,1	0,2
2956	15	29,2	14,5	0,5	0,1	0,2	2,0	2,5	5,5	0,8	2,0	1,5	0,3	0,4
3058	16	40,1	22,5	1,0	0,0	0,1	3,4	3,0	6,2	1,1	2,4	1,8	0,3	0,2
3038	17	49,3	28,0	2,0	0,1	0,1	4,8	2,0	8,2	1,4	3,5	2,8	0,6	0,5
2469	18	58,7	33,7	3,2	0,4	0,4	7,0	1,8	9,2	1,7	4,9	3,0	0,5	0,4
2223	19	64,6	33,4	4,1	0,5	0,5	8,6	1,4	9,4	1,5	4,2	3,3	0,4	0,3
2271	20	69,7	34,0	4,9	0,6	0,9	7,4	1,5	10,0	1,7	5,4	4,0	0,9	0,5
2354	21	83,2	33,0	4,8	0,5	0,6	6,3	1,4	9,0	1,3	3,9	4,1	0,6	0,3

4.2. Descriptive statistics and Cartesian and polar coordinate systems

Descriptive statistics are quantitative characteristics of data [70, 85-91]. To obtain the data results of descriptive statistics in Excel, in the section "Data," the method "Data analysis" was selected. The item "Descriptive statistics" was selected. In the menu of "Descriptive statistics," all values from the table "Alcohol " were set, and the place of output of values was indicated (Table 2 - Table 3). Similar actions were taken for the other drugs. After all the data, we were obtained. The result of Average, Standard error, Median, Moda, Standard deviation, Sampling variance, Excess, Asymmetry, Interval, Minimum, Maximum, Amount, and Account were prepared, namely, formatting. All numbers were reduced to "00.00".

Fig. 1 shows the structure of 13 drugs used by age in the Cartesian coordinate system. Fig. 2 shows the structure of 13 drugs used by age in the polar coordinate system.

Table 2
Descriptive statistics of the US drug use by age

Parametre	alcohol	marijuana	cocaine	crack	heroin	hallucinogen
Average	42,53	21,23	2,08	0,22	0,30	4,19
Standard error	8,57	4,19	0,63	0,08	0,09	0,96
Median	44,70	25,25	1,50	0,10	0,15	4,10
Moda	-	-	0,10	0,00	0,10	-
Standard deviation	27,12	13,24	2,00	0,25	0,29	3,04
Sampling variance	735,26	175,34	4,01	0,06	0,08	9,27
Excess	-1,29	-1,60	-1,77	-1,82	0,37	-1,66
Asymmetry	-0,08	-0,50	0,41	0,53	1,09	0,06
Interval	79,30	32,90	4,80	0,60	0,90	8,40
Minimum	3,90	1,10	0,10	0,00	0,00	0,20
Maximum	83,20	34,00	4,90	0,60	0,90	8,60
Amount	425,30	212,30	20,80	2,20	3,00	41,90
Account	10,00	10,00	10,00	10,00	10,00	10,00

Table 3
Descriptive statistics of the US drug use by age (continue)

Parametre	inhal ant	pain-releiver	oxycontin	tranquilizer	stimulant	meth	sedative
Average	2,03	6,58	1,01	2,77	2,18	0,38	0,31
Standard error	0,18	0,95	0,20	0,60	0,46	0,09	0,04
Median	1,90	7,20	1,20	2,95	2,30	0,35	0,30
Moda	2,50	-	0,10	-	-	0,10	0,20
Standard deviation	0,58	3,02	0,62	1,89	1,46	0,28	0,14
Sampling variance	0,34	9,10	0,39	3,58	2,14	0,08	0,02
Excess	-1,40	-1,48	-1,39	-1,48	-1,56	-0,28	-1,17
Asymmetry	0,40	-0,46	-0,50	-0,13	-0,09	0,41	0,10
Interval	1,60	8,00	1,60	5,20	3,90	0,90	0,40
Minimum	1,40	2,00	0,10	0,20	0,20	0,00	0,10
Maximum	3,00	10,00	1,70	5,40	4,10	0,90	0,50
Amount	20,30	65,80	10,10	27,70	21,80	3,80	3,10
Account	10,00	10,00	10,00	10,00	10,00	10,00	10,00

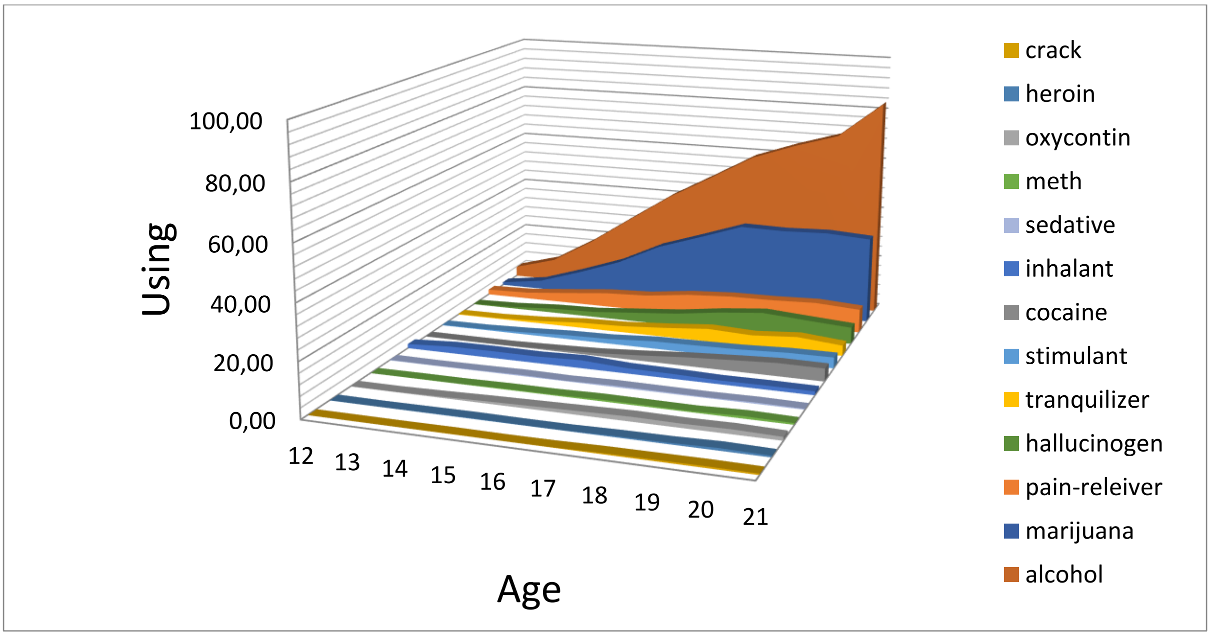

Figure 1: Visualization of drug use by age in the Cartesian coordinate system

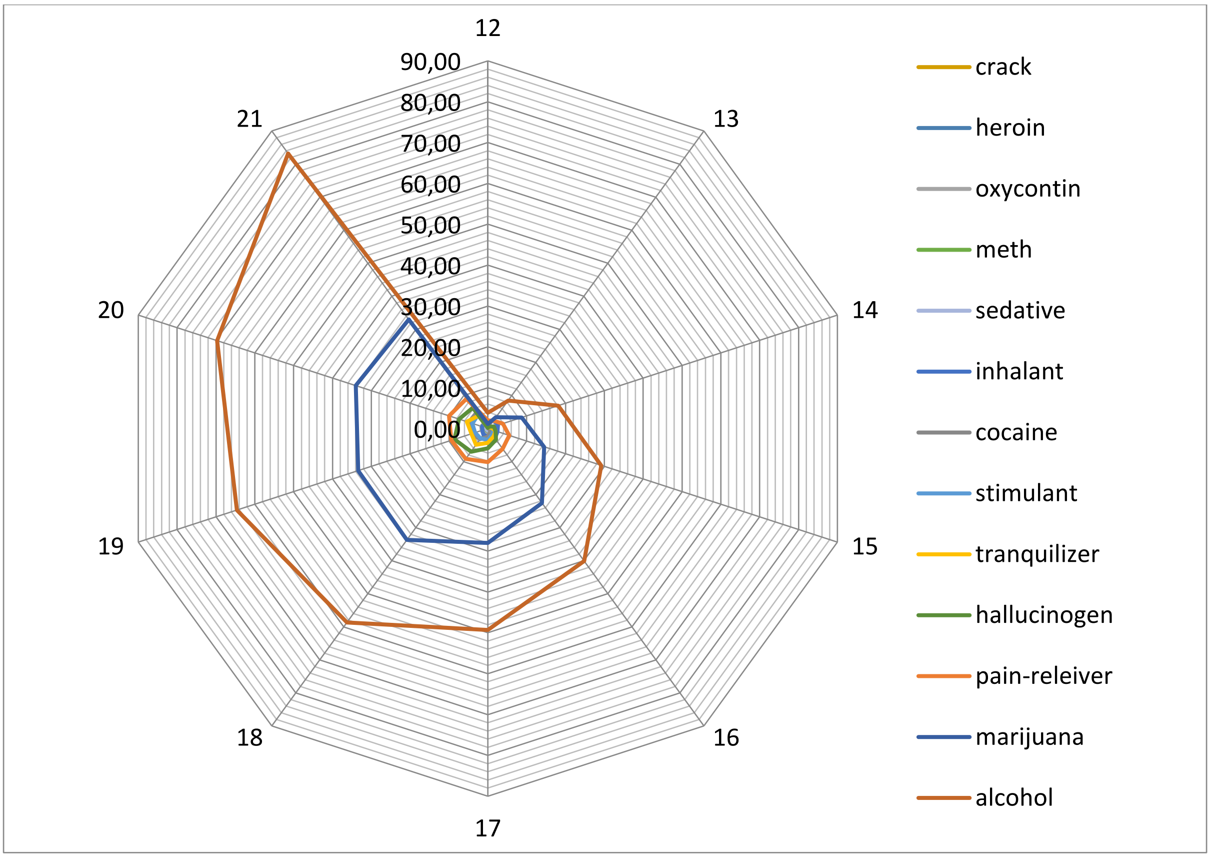

Figure 2: Visualization of drug use by age in the polar coordinate system

4.3. Histogram and cumulative

We consider the example of marijuana use. To construct a histogram, the values of the boundaries of the intervals are indicated, and rectangles are constructed on their basis, the height of which is proportional to the frequencies (or frequencies). Data Analysis >> Histogram was opened, and parameters were set. Fig. 3 show the histogram of the frequency of marijuana use by age. Fig. 4 shows cumulative of the frequency of marijuana use by age.

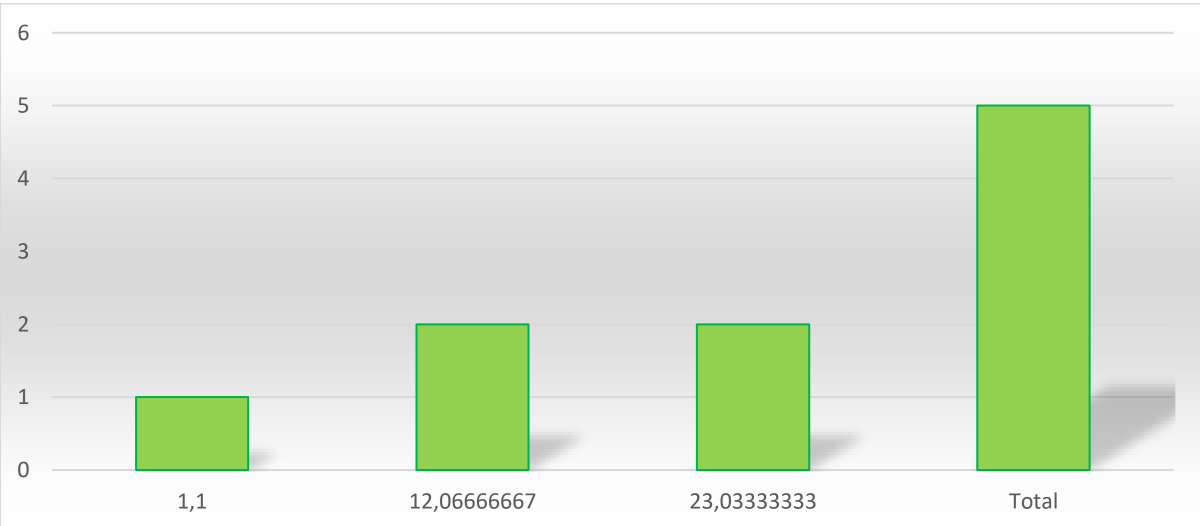

Figure 3: Histogram of the frequency of marijuana use by age

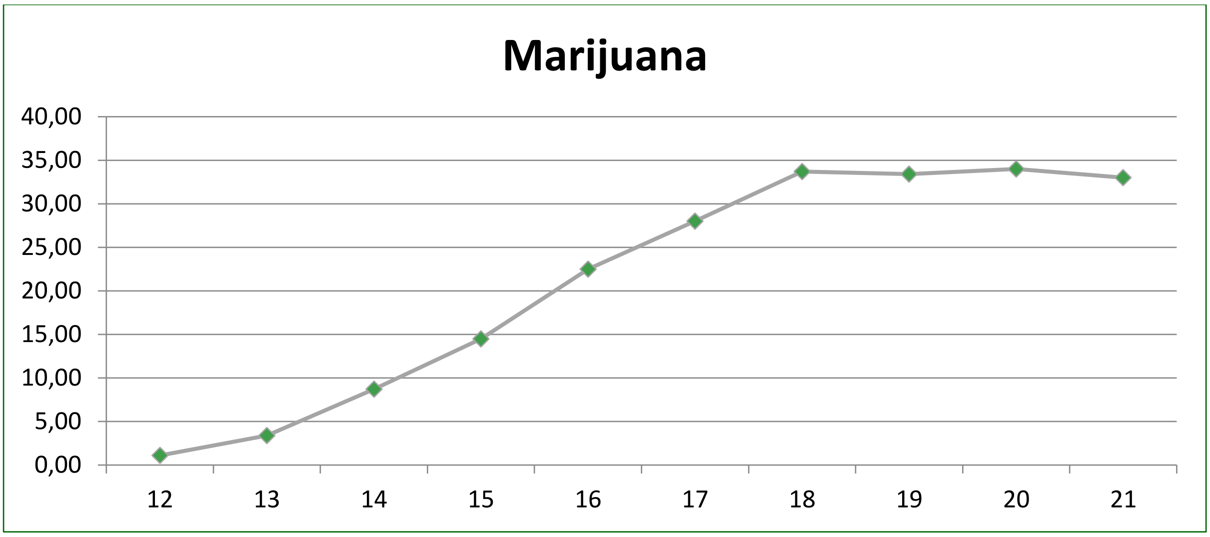

Figure 4: Cumulative the frequency of marijuana use by age in the Cartesian coordinate system

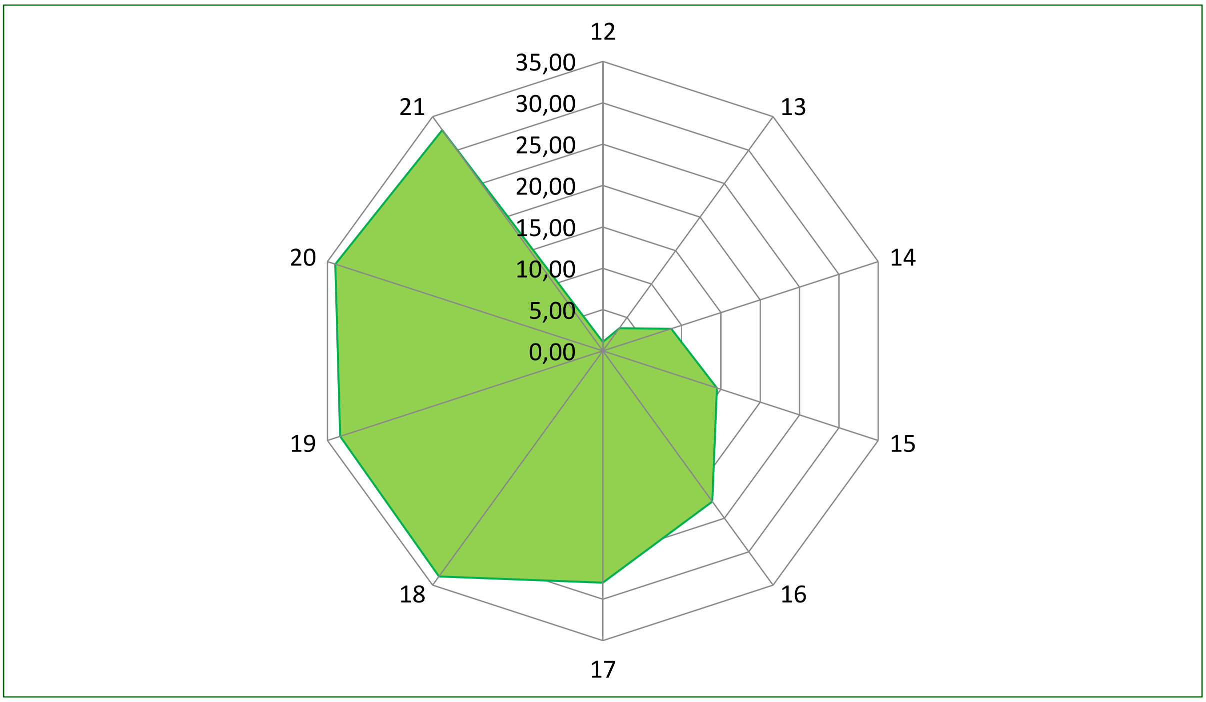

Figure 5: Cumulative of the frequency of marijuana use by age in the polar coordinate system

5. Discussions

Two smoothing methods classes differ in approaches. The first approach is called analytical. Based on visual analysis, the researcher can set a general view of the function, believing that its graph corresponds to the nature of the trend. The second approach is called algorithmic. Here, researchers look at the trend through the use of various smoothing procedures. The algorithmic approach uses the following methods [70, 72, 82-84].

- Simple or ordinary moving average;
- Weighted moving average;
- Exponential smoothing;
- Median smoothing.

Figure 6 shows the results of using the simple moving average method for marijuana use.

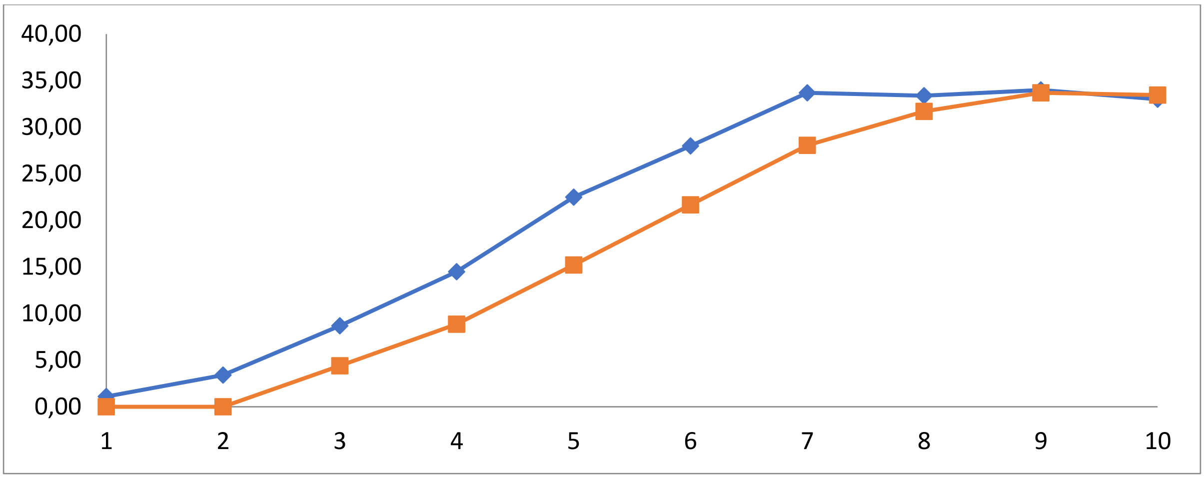

Figure 6: The simple moving average of marijuana use by age

Along with simple moving averages, polynomial or weighted averages are also used [92-98]. These methods allow us to describe the main trend of the series more accurately because when calculating the weighted average, each level of the series within the smoothing interval is assigned a certain weight, depending on the distance to the middle of the interval.

The result for marijuana uses by age is shown in Fig. 7, where the moving average is realized using the minimum smoothing interval w = 5.

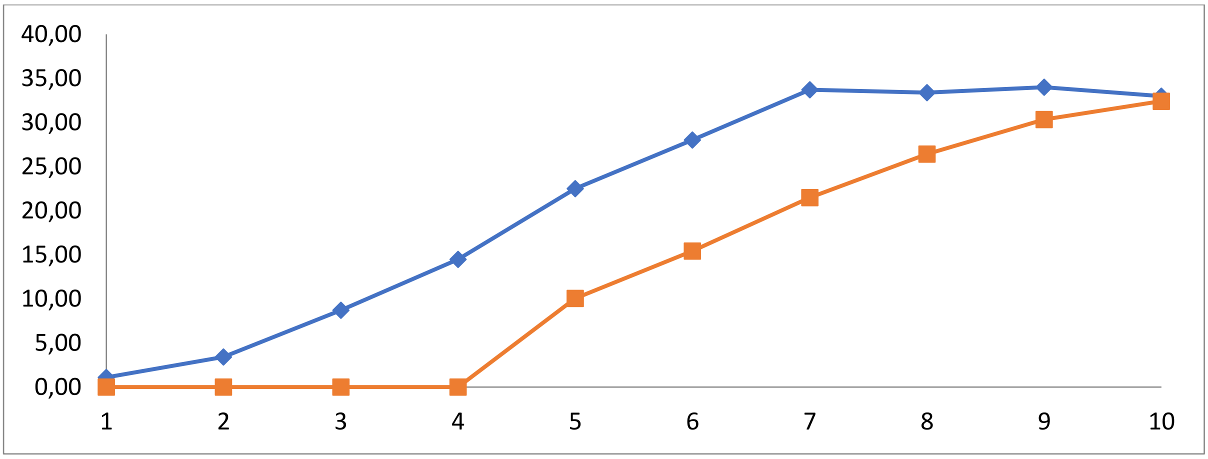

Figure 7: The moving average of marijuana use by age at w=5

Fig. 8 shows the exponential smoothing result of marijuana use by age at alpha = 0.1.

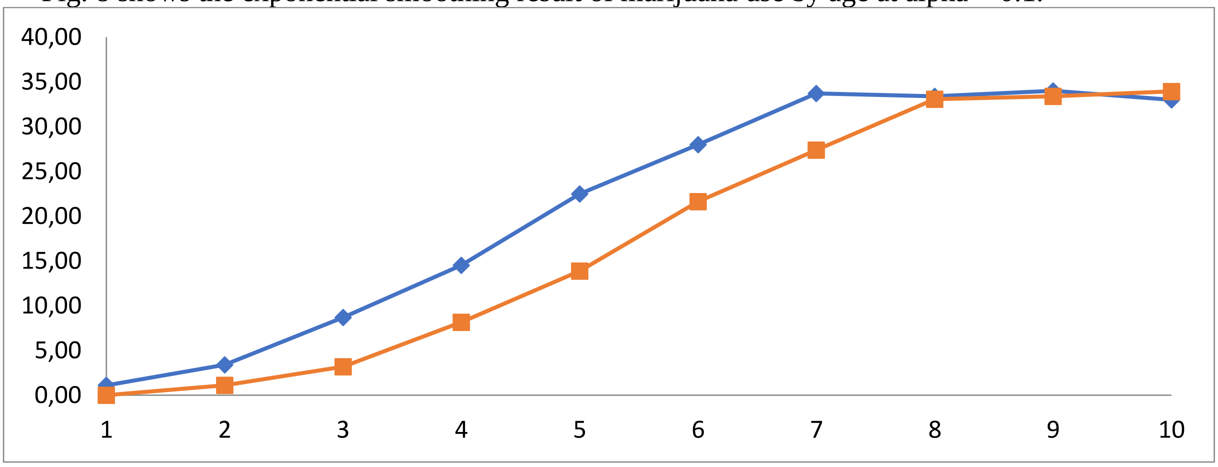

Figure 8: The exponential smoothing of marijuana use by age at alpha = 0.1

5.1. Median filtration

Median smoothing and turning point criteria according to the formula: = IF ((AC3> AA3); (AC3> AE3); OR (IF (AC3 <AA3); (AJ17 <AE3)))) Intervals w = 2, w = 3, w = 4, w = 5 were taken, because there are 10 points in the column. The median with the interval w = 2 is simply transferred from the table for the first value. We set the median function for the next row in the table. We substitute the values from the first and second rows of the data set in the table into its formula. After that, the function was "stretched" to the entire table. And check that all values in the formula are set correctly.

For a median with an interval of 3, all the same, actions are performed but take into account the interval. The first and last rows are duplicated from the table's data set, as it cannot be calculated in this case. For a median with an interval of 4, all the same, actions are performed but take into account the interval. Also, the first two and last rows are duplicated from the table with the data set, as they cannot be calculated in this case. For a median with an interval of 5, all the same, actions are performed but take into account the interval. Also, the first two and last rows are duplicated from the table with the data set, as they cannot be calculated in this case.

The result of median smoothing of all 13 drug uses is shown in Fig.9-Fig.10.

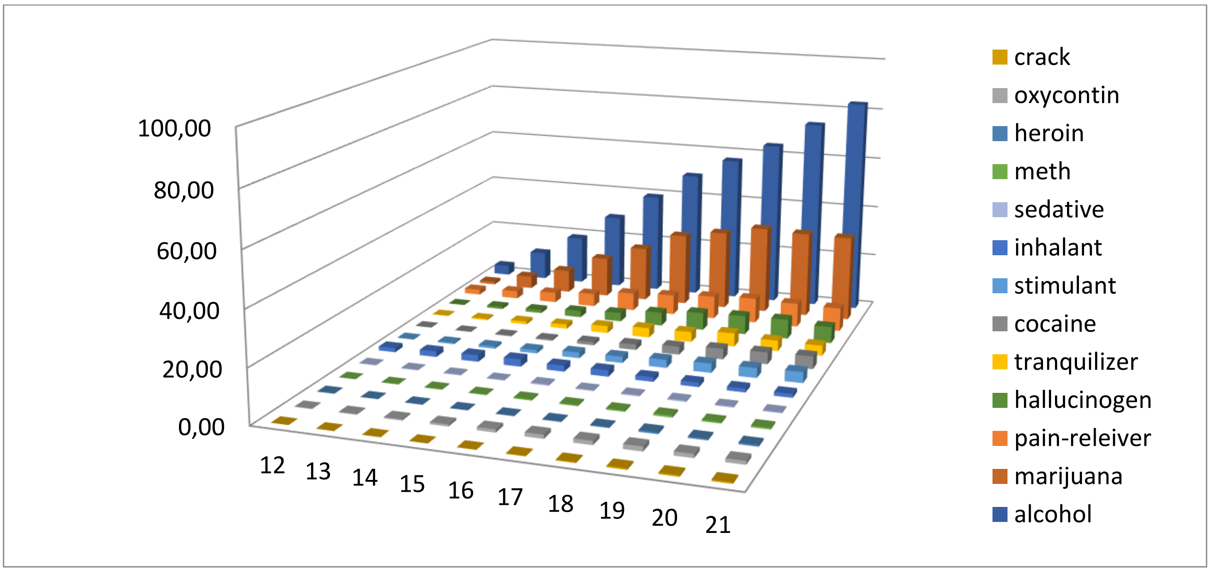

Figure 9: The visualization for all 13-drug use by the age of the median smoothing results at w = 3

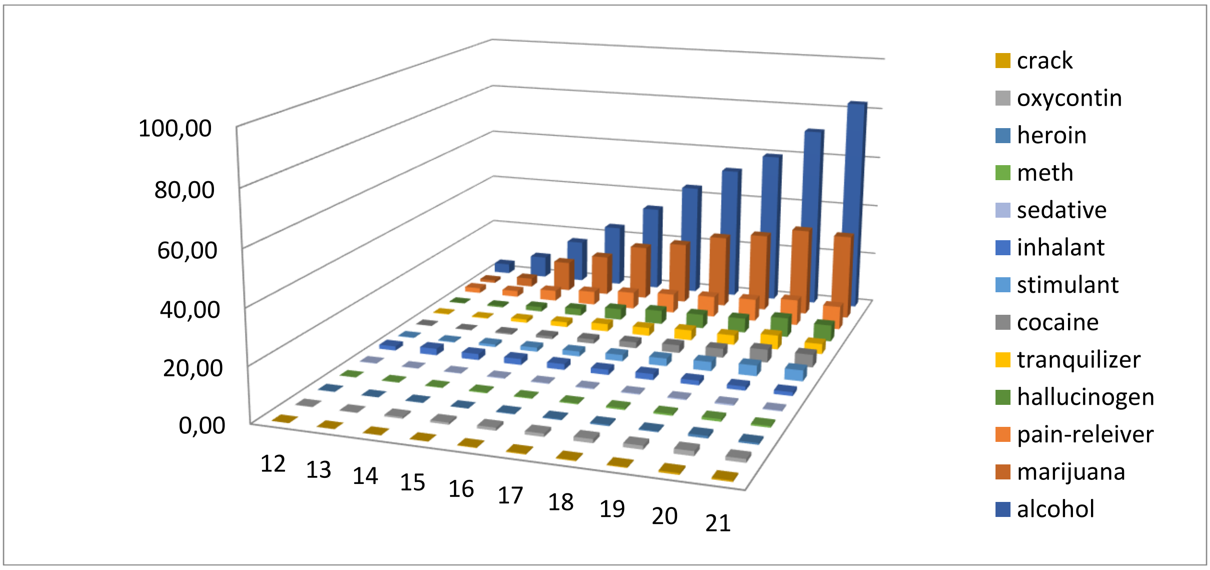

Figure 10: The visualization for all 13-drug use by the age of the median smoothing results at w = 5

5.2. Properties of moving average method

We select the "Data analysis" menu to perform the moving average method. In the "Data analysis" menu, we use the parameter "Moving average". We use the " Input interval " in the "Moving Average" menu; we use the "Input interval". We set a column with the drug use values. The interval is set. And the place of output of the schedule is set. The output of the schedule. Fig. 11 show the results for all 13-drug use by the age of the moving average smoothing.

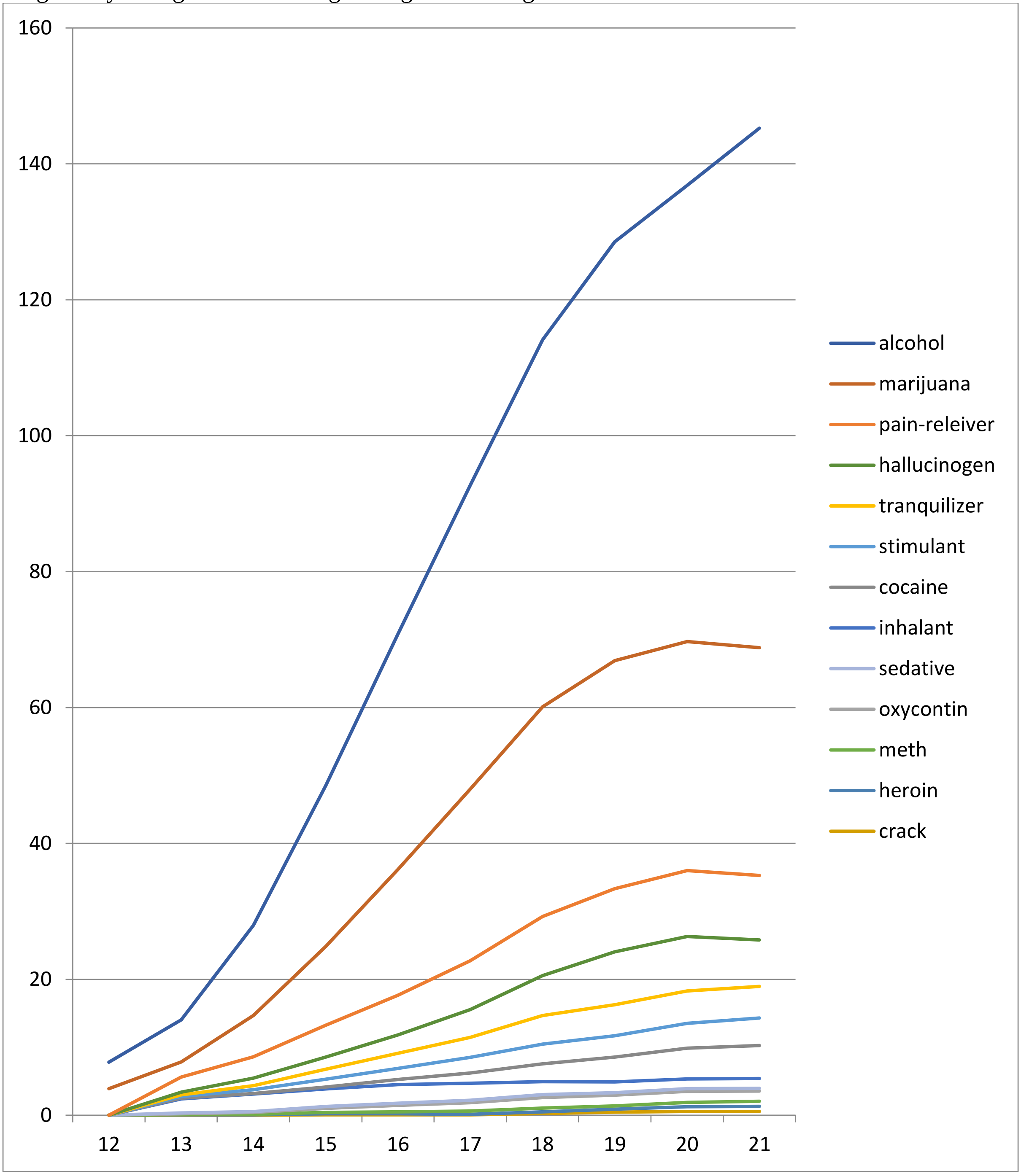

Figure 11: The results of the moving average smoothing at w = 3 for use level of all drug types by age

The moving average method was performed on the same principle. We smoothed the usability indicators by a moving average of all indicators for all age categories (Fig.11) and smoothing alcohol consumption only at different intervals (Fig.12).

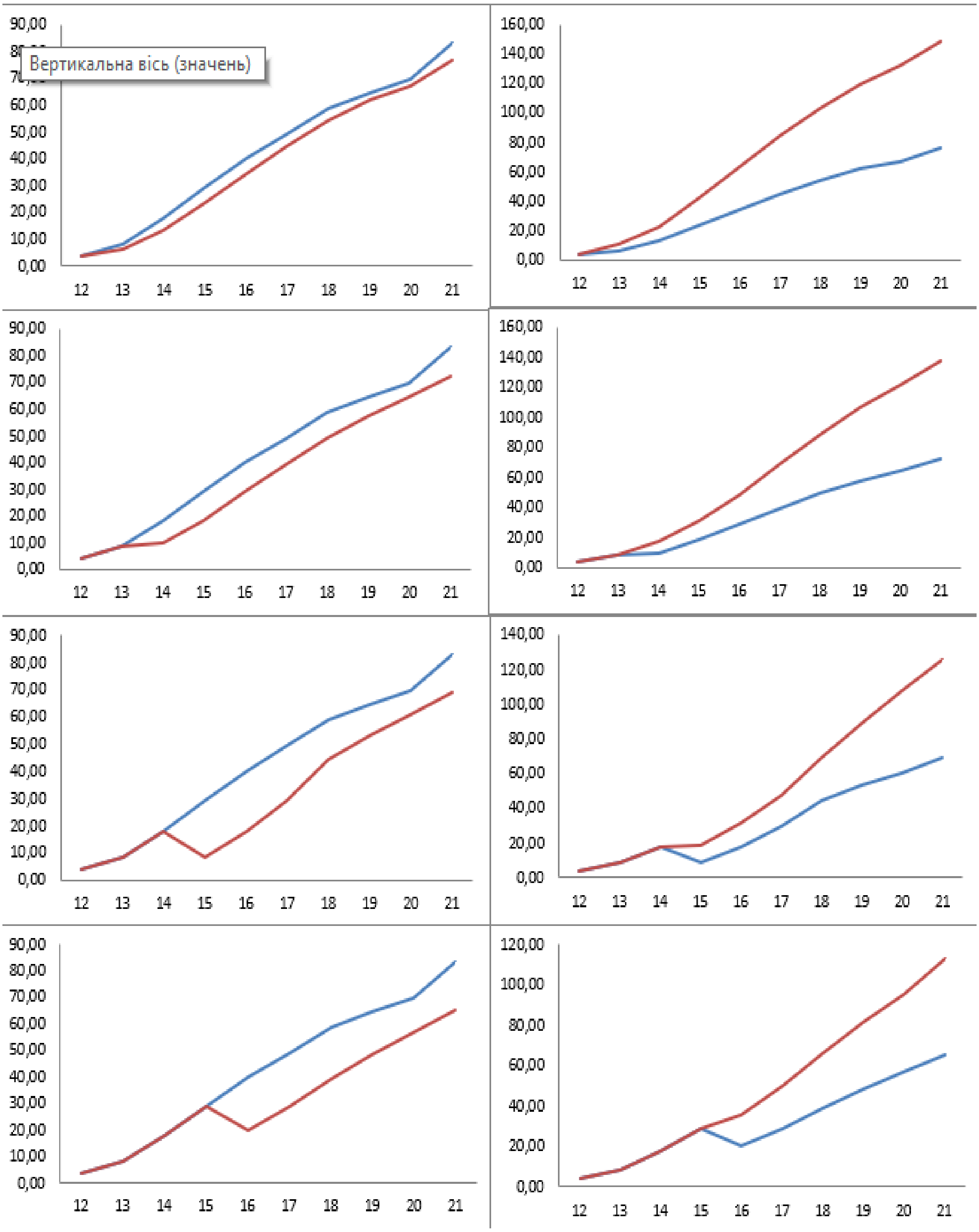

Figure 12: The results of the moving average smoothing at the different intervals for alcohol consumption by age

5.3. Exponential smoothing

As an illustration of execution, we use the "Data analysis" menu, and we choose the "Exponential smoothing" at alpha = 0.2. The result of exponential smoothing the level of use of all types of drugs by age is presented in the form of a graph (Fig.13).

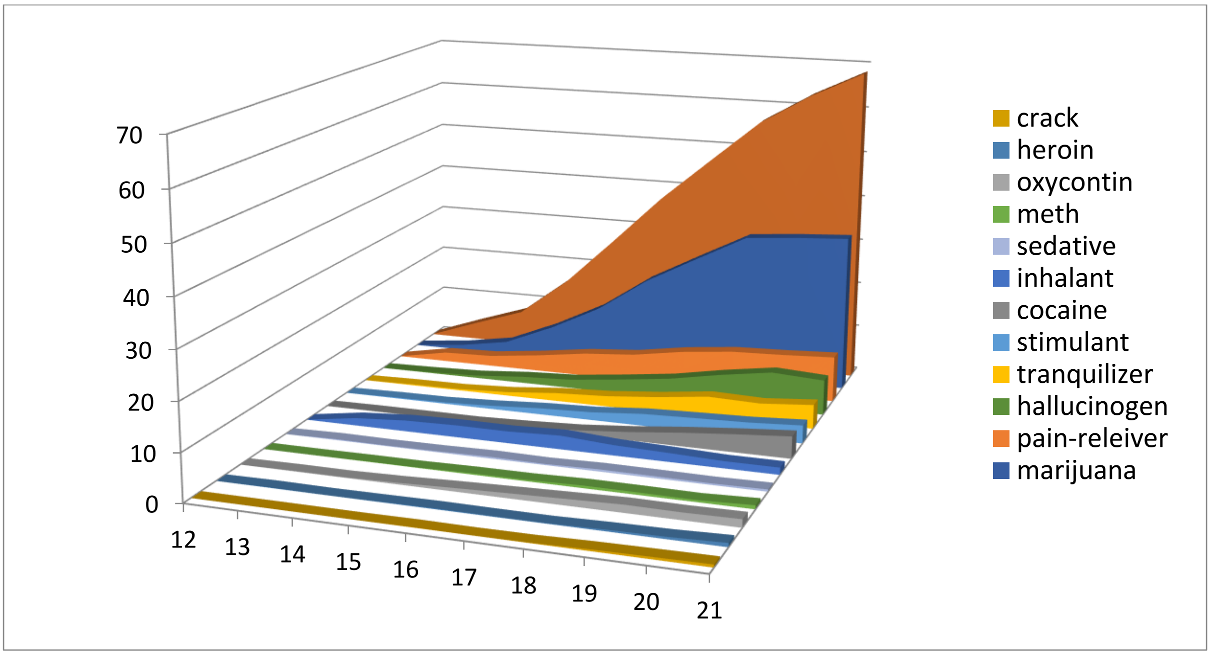

Figure 13: The results of exponential smoothing for use level of all drug types by age

5.4. Pollard formula

In the case of marijuana use, we use intervals w= 2, 3, 4, 5 (Fig.14). For each interval, a formula was given where 100 per cent of the significance was divided between age categories. For example, at intervals of 2, 100% of the significance is divided into the highest 60% and 40% and multiplied by giving more importance to the younger age group. For w = 3 division 50%, 30%, 20%. For w = 4 division 35%, 30%, 25%, 10%. For w = 5 division 35%, 30%, 20%, 10%, 5%.

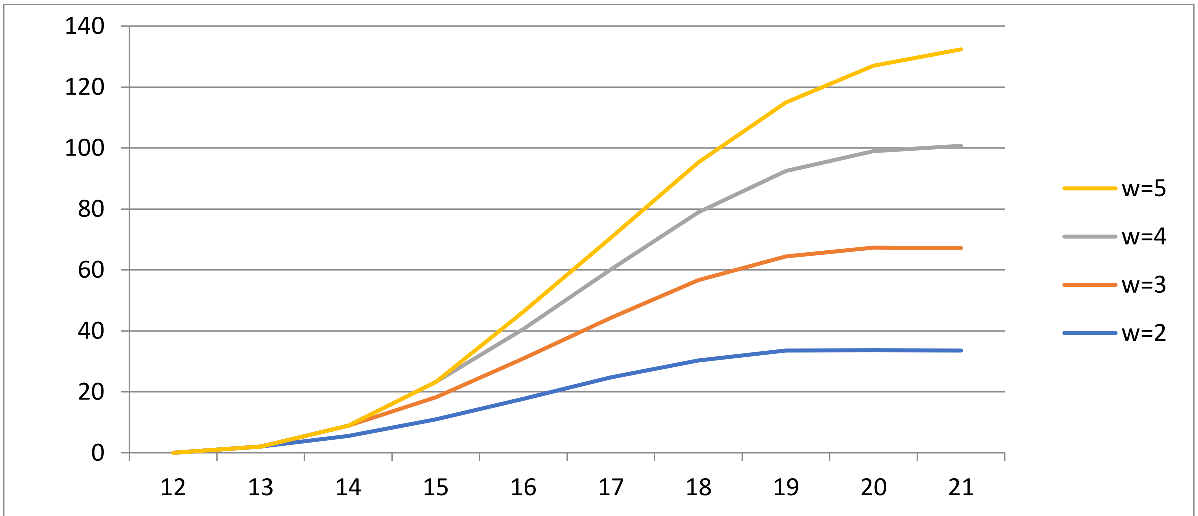

Figure 14: The results of smoothing by Pollard formula for marijuana use by age

5.5. Cluster analysis

A matrix of indicators by age categories: 12, 15, 18, 21; and indicators of the use of these age categories: alcohol, marijuana, cocaine, crack. We created a table "object-property" for cluster analysis, shown in Table 4. We reduced the data of the obtained matrix to the form "0.0".

Table 4
The object-property table

Age	Alcohol	Marijuana	Cocaine	Crack
12	3.9	1.1	0.1	0.0
15	29.2	14.5	0.5	0.1
18	58.7	33.7	3.2	0.4
21	83.2	33.0	4.8	0.5

We have constructed a proximity matrix (Table 5). For convenience, the age of the juvenile was replaced by a unique number from 1 to 4. We measured the distance between objects in the Euclidean metric. We built on Euclidean space by the following formula: = ROOT ((x2-x1) ^ 2 + (y2-y1) ^ 2) [40-41, 67, 115-123]. We reduced the data of the obtained matrix to the form "00.00".

Table 5
Creating proximity matrix

	1	2	3	4
1	0.00	13.41	13.41	0.41
2	13.41	0.00	19.39	2.72
3	13.41	19.39	0.00	1.60
4	0.41	2.72	1.60	0.00

The association of clusters is carried out in Table 6- Table 7. The nearest neighbours were searched; namely, the values between which the distance is the smallest were chosen. In this example, 1, 4. A new matrix was created where these values were combined. And again, we are looking for the shortest distance. And then came the result where the distance between neighbours was 19.39. The procedure for merging clusters is presented in Table 8. Drawing horizontal lines in the plane of the dendrogram at a given height, in this case, allows you to select individual clusters [99-114] (Fig. 15).

Table 6
The merging 3 clusters

Juvenile	1, 4	2	3
1, 4	0.00	13.41	13.41
2	13.41	0.00	19.39
3	13.41	19.39	0.00

Table 7
The merging 2 clusters

Juvenile	1, 4,2	3
1, 4, 2	0.00	19.39
3	19.39	0.00

Table 8
The procedure for merging clusters

Steps	Merge	Node	Metric
1	1+4	5	0.41
2	1+4+2	6	13.41
3	1+4+2+3	7	19.39
1	1+4	5	0.41

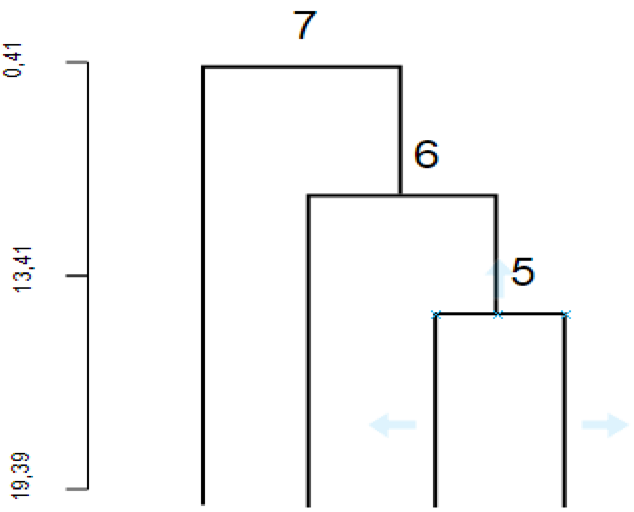

Figure 15: The results of cluster analysis for use by age of alcohol, marijuana, cocaine, and crack

At the level of 19.39, there are 3 clusters:
1 - objects 1, 4
2 - object 2
3 - object 3

At the level of 13.41, there are 2 clusters:
1 - objects 1, 4, 2
2 - object 3

At the level of 0.41, there is 1 cluster:
1 - objects 1, 4, 2, 3

Thus, we provide an overview of the drug use of 13 minors in the United States between the ages of 12 and 21 during the lockdown. There is a general encouraging trend towards a general decline in youth drug use. On the other hand, the availability and popularity of drugs such as marijuana and alcohol are concerned. Regardless of the type of drug, their use among young people is usually reduced during quarantine. A particularly noticeable reduction in consumption disorders was demonstrated by persons aged 12–14 years. In addition, given the evidence that decentralized areas have less access to drug treatment services and are more vulnerable to drug cartels, the importance of implementing critical policy and educational measures in the 16-21 age group should be emphasized. It is also not superfluous to conduct in schools the subject of first aid for drug overdoses, such as naloxone, further care; rescue breathing; call an ambulance. These are the most valuable things to study, as most overdose deaths occur at home, and the only rescue help can come from friends or relatives. If they have enough knowledge to provide such first aid, it will reduce the death rate from overdoses.

6. Conclusions

Using descriptive statistics, data visualization, smoothing (Kendall, Pollard, median, exponential), data correlation, and cluster analysis, this data set study suggests that drug use and subsequent overdoses remain critical and challenging for US public health under the impact of the pandemic of COVID-19. Variations and trends in drug overdose mortality depend on the popularity of drugs in different generations. Comparing drug use trends among different generations of young people revealed that generations of baby boomers suffer more than other generations. It has been established that minors aged 16-21 who have started using drugs before quarantine, in most cases, will continue to use drugs after quarantine. It will be facilitated by active communication and attending parties—the risk of increasing levels of violence and aggression in society increases, and the likelihood of overdose increases. For consumers aged 12-16, quarantine conditions have benefited by lowering the trend of drug use in later life. The decline in illicit drug use among young people and the lower prevalence of drug use during the lockdown during 2019-2020 are encouraging signs. However, the increase in juvenile drug use in decentralized areas, which exceeded that in urban areas during quarantine, and persistently limited access to drug treatment services in rural areas, is a concern. The state should also implement additional policy and educational measures to prevent not only marijuana use but also other serious drugs such as cocaine/crack and heroin among adolescents. It will positively reduce drug addiction among young people, which will help reduce mortality from drugs in the United States in general. After quarantine, the drug trafficking environment will return to its previous levels of illicit trafficking and quickly reach its previous level of crime.

7. References

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