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Row and Column Effects Modelling of Elderly Age Groups and Chronic Health Problem on COVID-19

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ABSTRACT

Statistical analysis of COVID-19 data from China and NYC, using log-linear models, helps identifying high-risk groups like those aged over 65 and individuals with chronic health issues. According to the results of row effects model applied to the COVID-19 data set of China, we conclude that when the age group increases by one unit, the risk of getting COVID-19 disease is approximately 8 times higher for the patients having Chronic Obstructive Pulmonary Disease (COPD) than patients having hypertension, 9.37 times higher than patients with coronary heart disease, 13.37 times higher than patients having diabetes and cerebrovascular diseases and 10.16 times higher than patients having other diseases. According to the results of column effects model applied to the COVID-19 data set of NYC, we conclude that when the age group increases by one unit, the risk of death from the COVID-19 disease is approximately 2 times higher for the patients having choric health problem than the patients not having a chronic health problem. We believe that the empirical findings of the presented study will guide the policymakers to make provision for these disadvantageous groups for COVID-19 disease.

Keywords: Categorical data analysis, Row effects model, Column effects model, COVID-19 data.

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Introduction

In December 2019, pneumonia caused by the newly identified SARS-CoV-2 factor was identified as coronavirus disease 2019 (COVID-19) in the pneumonia epidemic, which is the center of Wuhan city of China and a large number of people became infected (WHO Report, 2020; CDC(Center for Disease Control) Report, 2020). COVID-19 is caused by a new type of coronavirus which was previously named 2019-nCoV by the World Health Organization (WHO). The transmission characteristics of COVID-19 appear to be similar to those of pandemic influenza. Transmission to human to human have been conformed and structural analysis suggests that SARS-CoV-2 might be able to bind to the angiotensin-converting enzyme 2 receptor in humans [1]. Incubation period was reported between 1 and 19 days [2].

The virus can spread from human to human through respiratory droplets and close contacts [2]. Many clinical studies of hospitalized patients have shown that at onset on COVID-19, patients frequently show symptoms such as fever, cough, sore throat, fatigue, shortness of breath, diarrhea and myalgia [3-6]. The incubation period of COVID-19 could be up to two weeks or longer [7].

COVID-19 morbidity and mortality rates differ from country to country and COVID-19 has been causing a potentially fatal disease as a global public health problem. It is stated that COVID-19 progresses severely in the elderly and comorbid. However, the disease severity was found to be higher in patients under the age of sixty and without chronic disease compared to influenza pneumonia. Liu et.al [8] found that elderly patients with COVID-19 are more likely to progress to severe disease. Likassa [9] also showed that age variation has a statistical significant associated with COVID-19.

According to CDC, those at high-risk for severe illness from COVID-19 are defined as: 65 years and older age groups; people who live in a nursing home or long-term care facility ; People of all ages with some underlying medical conditions; people with chronic lung disease or moderate to severe asthma, chronical heart disease, diabetes, liver disease; people who are immunocompromised; people with severe obesity; people with chronic kidney disease undergoing dialysis [10].

Sasson [11] investigated the relationship between age and COVID-19-related deaths in conjunction with other causes of mortality. The results obtained from the study, which utilized data from the United States, were employed for the estimation of death counts by age.

In the study by Ahrenfeldt et al. [12] the differences in COVID-19-related survival between genders across age groups and regions in Europe were investigated. According to the study, it was observed that the risk of mortality from COVID-19 was higher for men compared to women in almost all regions and age groups.

COVID-19 is ordinarily diagnosed based on positive SARS-CoV-2 nucleic acid test from respiratory tract specimen or based on clinical diagnosis.

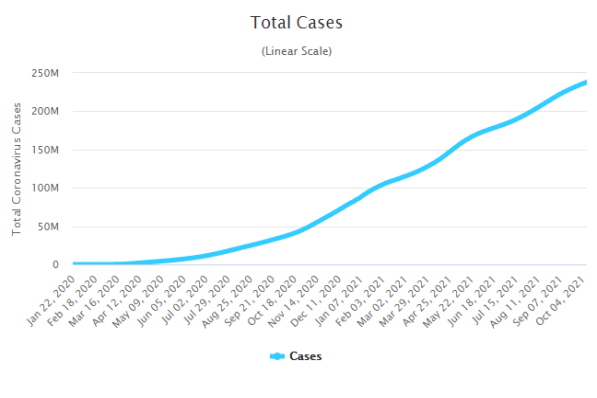

Figure 1. The plot of the cumulative counts of COVID-19 cases (worldwide).

Figure 1 displays the cumulative cases of COVID-19 for all countries as of 4th of October, 2021. This figure shows that there is linear trend in increment of the cases of COVID-19. It is clear that the effects of the pandemic cannot be understood deeply without data and its statistical modeling. This paper consists of two aims: the first is to introduce log-linear models such as row and column effects models which are very powerful to extract the relation between row and column variables. The second aim is to make new inferences using some up-to-date COVID-19 data from the literature. This article addresses the impacts of medical history, age, and underlying diseases on two COVID-19 data set.

The two way cross-classified COVID-19 data are analyzed in the context of ordinal information. First, the row effects model is applied to number of older patients infected positive COVID-19 test according to age and their medical history data set. We secondly analyze the number of deaths patients with positive COVID-19 test according to age and chronic disease status contingency table using the column effects model. ,

Methods

Row and Column Effects Models

Log-linear models for contingency tables treat all variables as nominal variables. But this situation, meaning that ordinal variables are considered as if they are nominal, yields misleading results. Because treating ordinal variables as nominal variables ignores the ordering information of the ordinal variables. In a $R \times C$ contingency table, consider both the row and column variables are ordinal, linear by linear association and uniform association models in the literature utilize the ordering information of the variables by row and column scores [13,14]. Goodman [15] first proposed the association models and illustrated how the models are applied cross-classification tables.

Row effects models

For the $R \times C$ cross-classification table, let n_{ij} denote the observed frequency in the ith row and jth column of the table($i = 1, 2, \ldots, R;\ j = 1, 2, \ldots, C$), and let E_{ij} denote the corresponding expected frequency under the model,

$$\log(E_{ij}) = u + u_{1(i)} + u_{2(j)} + \mu_i y_j \qquad (1)$$

This model is referred to as the Row Effects (RE) model with the following constraints,

$$\sum_{i=1}^{R} u_{1(i)} = \sum_{j=1}^{C} u_{2(j)} = \sum_{i=1}^{R} \mu_i = 0 \ .$$

The $\{\mu_i\}$ are called as the row effects parameters and the $\{y_j\}$ are the fixed column scores,

The independence model is the special case when $\mu_1 = \mu_2 = \cdots = \mu_R$. For analyzing the row effects model, the column scores are assigned to the categories of the column variable as, $y_1 < .. < y_R$.

The degrees of freedom (df) for testing the goodness of fit test has more $(R-1)$ than the independence model,

$$df = RC - [1 + (R-1) + (C-1) + (R-1)]$$
$$= (R-1)(C-2) \ .$$

The general log-odds ratio models are defined as:

$$ln\theta_{11} = ln\frac{E_{ij}E_{i+1,j+1}}{E_{i,j+1}E_{i+1,j}} = (\mu_{i+1} - \mu_i)(y_{j+1} - y_j)$$

For instance, for the case $i = 1, j = 1$, the log-odds ratio is

$$ln\theta_{11} = ln\frac{E_{11}E_{22}}{E_{21}E_{12}} = lnE_{11} + lnE_{22} - lnE_{12} - lnE_{21}$$
$$= \mu_1 y_1 + \mu_2 y_2 - \mu_1 y_2 - \mu_2 y_1$$
$$= \mu_1(y_1 - y_2) - \mu_2(y_1 - y_2)$$
$$= (\mu_1 - \mu_2)(y_1 - y_2) \ .$$

Then, the difference between the adjacent row parameters gives the odds ratios,

$$\theta_{ij} = Exp(\mu_{i+1} - \mu_i) \qquad (2)$$

For 2×2 sub-tables formed from adjacent rows, the row effects model satisfies the equality of odds ratios.

Column effects models

Analogously, consider a $R \times C$ cross-classification table in which the row variable has ordinal and the column variable is nominal,

$$\log(E_{ij}) = u + u_{1(i)} + u_{2(j)} + \tau_j x_i \qquad (3)$$

This model is referred as the Column Effects (CE) model with constraints,

$$\sum_{i=1}^{R} u_{1(i)} = \sum_{j=1}^{C} u_{2(j)} = \sum_{j=1}^{C} \tau_j = 0 \ .$$

The column effects model is defined as a simple log-linear model for this situation utilizes the orderings of the row variable. For analyzing the column effects model, the column scores are assigned to the categories of the row variable. $\{\tau_j\}$ is the jth column parameters and, $\{x_i\}$ is the ith row scores , $x_1 < \ldots < x_C$. This model has more $(C-1)$ parameters than the usual independence model, the df for testing the goodness of fit,

$$df = RC - [1 + (R-1) + (C-1) + (C-1)]$$
$$= (R-2)\,(C-1).$$

Let θ_{ij} denote the corresponding odds-ratio for $i = 1, \ldots, R-1;\ j = 1, \ldots, C-1$. As in the row effects model, the log-odds ratios are calculated through the adjacent column parameters as,

$$\theta_{ij} = Exp(\tau_{j+1} - \tau_j) \qquad (4)$$

For 2×2 sub-tables formed from adjacent columns, the column effects model satisfies the equality of odds ratios [16].

Although, choice of the row and column scores are assigned as the integer scores in practice, there is a no rule of thumb about choosing the scores for both row effects and column effects models.

Results

Analysis of China Covid-19 data

Countries across the world have been facing an important demographic structure from young to increasingly elderly populations. Unfortunately, elderly people worldwide also have been facing the risk of infected with COVID-19. Particularly, older adults who have severe underlying medical conditions like coronary heart disease, lung disease, diabetes or hypertension seem to be at higher risk for developing more serious complications from COVID-19 illness. It is noted that 8 out of 10 deaths reported in the U.S. have been in adults 65 years old and older.

Data consists of 63 older patients infected with laboratory confirmed COVID-19, described and analyzed the epidemiological and clinical characteristics of the older patients with COVID-19 infection are directly taken from Niu et.al [17]. The authors collected the data on the 63 older patients infected with laboratory confirmed COVID-19, and analyzed the epidemiological and clinical characteristics of the older patients with COVID-19 infection. We only studied on medical history variable among several characteristics. Niu et.al [17] analyzed the data with some frequently used methods.

The row effects model is applied to data in Table 1. The expected frequencies under the row effects model are given in the square brackets. The aim of applying this model is to estimate how the presence of a medical history increases the likelihood of age groups than others. The odds of being $(i+1)th$ medical history than ith medical history is θ_{ij} times greater for all age groups.

Table 1. Number of older patients infected positive COVID-19 test according to age and their medical history. (The number in the parentheses of table is the ML fitted values that satisfy the row effects model)

Medical history	Age		
	50-64	65-79	+80
Hypertension	7 (7.369)	12 (11.261)	3 (3.369)
Coronary heart disease	3 (3.019)	4 (3.963)	1 (1.019)
COPD	0 (0.21)	3 (2.58)	6 (6.21)
Diabetes	2 (2.397)	3 (2.205)	0 (0.397)
Cerebrovascular disease	3 (2.397)	1 (2.205)	1 (0.397)
Other	6 (5.608)	6 (6.785)	2 (1.608)

The design matrix for the row effects model contains seven columns where 5 out of 7 columns is represented the row effects parameters. Sum of row effects parameters is set to zero assuming equidistant scores for the categories of the variables [18].

Table 2. Design matrix for the row effects model

Age Groups	Medical history	μ_1	μ_2	μ_3	μ_4	μ_5
1	1	1	0	0	0	0
1	2	2	0	0	0	0
1	3	3	0	0	0	0
2	1	0	1	0	0	0
2	2	0	2	0	0	0
2	3	0	3	0	0	0
3	1	0	0	1	0	0
3	2	0	0	2	0	0
3	3	0	0	3	0	0
4	1	0	0	0	1	0
4	2	0	0	0	2	0
4	3	0	0	0	3	0
5	1	0	0	0	0	1
5	2	0	0	0	0	2
5	3	0	0	0	0	3
6	1	-1	-1	-1	-1	-1
6	2	-2	-2	-2	-2	-2
6	3	-3	-3	-3	-3	-3

Table 3. The goodness of fit statistics, degrees of freedom and p-value of model

Model	G^2	df	p-value
Row effects	3.53	5	0.617

The row effects model holds for data and the model equation would be:

$$\log(E_{ij}) = 1.517 - 0.114RE1 - 0.266RE2 + 1.971RE3 - 0.622RE4 - 0.622RE5 - 0.347RE6 + 0.040Hypertension - 0.701Coronary\ heart\ disease - 5.603COPD - 0.576Diabetes - 0.576Cerebrovascular\ disease + 6.84Other + 0.554age(50-64) + 1.092age(65-79) - 1.646age(+80).$$

Estimates of the row effects parameters with their standard errors are given in Table 4. Odds ratios over the row effects parameters are illustrated in Table 5.

Table 4. Parameter estimations and odds ratios for the row effects model

Row Effects Parameter	Estimation	Standard Error	Z
μ_1	-0.114	0.348	-0.328
μ_2	-0.266	0.494	-0.538
μ_3	1.971	0.628	3.141
μ_4	-0.622	0.629	-0.989
μ_5	-0.622	0.629	-0.989
μ_6	-0.347	0.799	0.434

Odds ratios calculated over adjacent row effects parameters as in Equation 2.

From the row effects parameters, the odds that an observation will fall in column *j* rather than in column *j*+1, given that it is in row *i* could be calculated. $\theta_{ij} = Exp(\mu_{i+1} - \mu_i)$ are given in Table 5. For example *i*=1 ; *j*=2, the odds ratio is $\theta_{ij} = Exp(\mu_2 - \mu_1) = Exp(-0.266 + 0.114) = 0.86$ (1/0.86=1.16).

Table 5. Odds ratios for the row effects

i,j	Odds ratio	i,j	Odds ratio
1-2	1.16	2-6	1.08
1-3	8.04	3-4	13.37
1-4	1.66	3-5	13.37
1-5	1.66	3-6	10.06
1-6	1.26	4-5	1
2-3	9.37	4-6	1.32
2-4	1.43	5-6	1.32
2-5	1.43		

As the age group increases, the risk of incidence does not differ much in those with chronic disease, except for COPD disease.

Table 6. Pairwise comparison of medical history by their odds ratios

Compared medical history	Odds ratio
Hypertension and Coronary heart disease	$\hat{\theta}_1 = \frac{E_{11}\times E_{22}}{E_{12}\times E_{21}} = \frac{E_{12}\times E_{23}}{E_{13}\times E_{22}} = 0.859 \rightarrow \frac{1}{0.859} = 1.16$
Hypertension and COPD	$\hat{\theta}_2 = \frac{E_{11}\times E_{32}}{E_{12}\times E_{31}} = \frac{E_{12}\times E_{33}}{E_{13}\times E_{23}} = 8.04$
Hypertension and Diabetes	$\hat{\theta}_3 = \frac{E_{11}\times E_{42}}{E_{12}\times E_{41}} = \frac{E_{12}\times E_{43}}{E_{13}\times E_{42}} = 0.602 \rightarrow \frac{1}{0.602} = 1.66$
Hypertension and Cerebrovascular disease	$\hat{\theta}_4 = \frac{E_{11}\times E_{52}}{E_{12}\times E_{51}} = \frac{E_{12}\times E_{53}}{E_{13}\times E_{52}} = 0.602 \rightarrow \frac{1}{0.602} = 1.66$
Hypertension and Other	$\hat{\theta}_5 = \frac{E_{11}\times E_{62}}{E_{12}\times E_{61}} = \frac{E_{12}\times E_{63}}{E_{13}\times E_{62}} = 0.792 \rightarrow \frac{1}{0.792} = 1.26$
Coronary heart disease and COPD	$\hat{\theta}_6 = \frac{E_{21}\times E_{32}}{E_{22}\times E_{31}} = \frac{E_{22}\times E_{33}}{E_{23}\times E_{32}} = 9.36$
Coronary heart disease and Diabetes	$\hat{\theta}_7 = \frac{E_{21}\times E_{42}}{E_{22}\times E_{41}} = \frac{E_{22}\times E_{43}}{E_{23}\times E_{42}} = 0.701 \rightarrow \frac{1}{0.701} = 1.43$
Coronary heart disease and Cerebrovascular disease	$\hat{\theta}_8 = \frac{E_{21}\times E_{52}}{E_{22}\times E_{51}} = \frac{E_{22}\times E_{53}}{E_{23}\times E_{52}} = 0.701 \rightarrow \frac{1}{0.701} = 1.43$
Coronary heart disease and other	$\hat{\theta}_9 = \frac{E_{21}\times E_{62}}{E_{22}\times E_{61}} = \frac{E_{22}\times E_{63}}{E_{23}\times E_{62}} = 0.922 \rightarrow \frac{1}{0.922} = 1.08$
COPD and Diabetes	$\hat{\theta}_{10} = \frac{E_{31}\times E_{42}}{E_{32}\times E_{41}} = \frac{E_{32}\times E_{43}}{E_{33}\times E_{42}} = 0.0748 \rightarrow \frac{1}{0.0748} = 13.37$
COPD and Cerebrovascular disease	$\hat{\theta}_{11} = \frac{E_{31}\times E_{52}}{E_{32}\times E_{51}} = \frac{E_{32}\times E_{53}}{E_{33}\times E_{52}} = 0.0748 \rightarrow \frac{1}{0.0748} = 13.37$
COPD and other	$\hat{\theta}_{12} = \frac{E_{31}\times E_{62}}{E_{32}\times E_{61}} = \frac{E_{32}\times E_{63}}{E_{33}\times E_{62}} = 0.09984 \rightarrow \frac{1}{0.0984} = 10.16$
Diabetes and Cerebrovascular disease	$\hat{\theta}_{13} = \frac{E_{41}\times E_{52}}{E_{42}\times E_{51}} = \frac{E_{42}\times E_{53}}{E_{43}\times E_{52}} = 1$
Diabetes and other	$\hat{\theta}_{14} = \frac{E_{41}\times E_{62}}{E_{42}\times E_{61}} = \frac{E_{42}\times E_{63}}{E_{43}\times E_{62}} = 1.32$
Cerebrovascular disease and other	$\hat{\theta}_{15} = \frac{E_{51}\times E_{62}}{E_{52}\times E_{61}} = \frac{E_{52}\times E_{63}}{E_{53}\times E_{62}} = 1.32$

However, as the age group increases, the risk of COVID 19 is 8,04 times higher in patients with COPD disease than in patients with hypertension, 9.37 times higher in patients with coronary heart disease, 13.37 times higher in patients with diabetes and Cerebrovascular disease and 10.16 times more in patients with other diseases. The odds ratio can also be calculated by using the ML fitted values that satisfy the row effects model, given in Table 6.

The odds for Hypertension (i=1) and COPD (i=3)

For the age groups 50-64 (j=1) and 65-79 (j=2),

$$\theta_2 = \frac{7.369 \text{ x } 2.58}{11.261 \text{ x } 0.21} = 8.04$$

For the age groups 65-79 (j=2) and ≥80 (j=3),

$$\theta_2 = \frac{11.261 \text{ x } 6.21}{3.369 \text{ x } 2.58} = 8.04$$

This calculation can be made through parameter estimates such as:

$$\theta_{ij} = Exp(\mu_3 - \mu_1) = Exp(1.971 + 0.114) = 8.04.$$

Note that the adjacent pairs have equal odds ratios. Entire odds ratio calculations under the row effects model is true are given in Table 6.

The pairwise comparison of medical diseases tells us that a patient with diabetes is 13.37 times more likely to get COVID 19 than a patient with COPD disease.

Similarly, a patient with COPD is 13.37 times more likely to have COVID 19 positive than a patient with Cerebrovascular disease in all age groups. The odds ratio equals 1 for Diabetes and Cerebrovascular diseases indicates that these diseases under study are equally likely to occur in entire age groups.

Analysis of NYC Covid-19 data

World case fatality rate of the ongoing COVID-19 pandemic was 7.07 as of May 9, 2020 (https://ourworldindata.org/mortality-risk-covid#the-case-fatality-rate). The case fatality rate is the number of confirmed deaths divided by the number of confirmed cases. Mortality rate is extremely higher in country with older-aged population, COVID-19 mortality risk is highly concentrated at older ages, particularly those aged 80+ [19].

We applied the column effects model to number of deaths patients with positive COVID-19 test according to age and chronic disease status data. The data in Table 7 is taken directly from NYC Health and, reflects events and activities as of April 14, 2020. Underlying illnesses include Diabetes, Lung Disease, Cancer, Immunodeficiency, Heart Disease, Hypertension, Asthma, Kidney Disease, and GI/Liver Disease. Distributions of underlying comorbidities of COVID-19 patients will help risk estimates. The concentration to age and chronic disease status in the age groups could be a helpful tool to predict the burden of critical cases and to arrange the hospital and other resources.

Table 7. Number of deaths patients with positive COVID-19 test according to age and chronic disease status. (The numbers in the parentheses of table are the ML fitted values that satisfy the column effects model)

Age	Chronic disease status		
	Underlying illnesses	No underlying illnesses	Underlying illnesses unknown
0-17	1 (0.797)	0 (0.151)	0 (0.052)
18-44	50 (52.659)	5 (4,831)	8 (5,509)
45-64	269 (261,799)	12 (11,638)	36 (43,563)
65-74	254 (261,236)	5 (5,626)	77 (69,137)
75+	458 (455,508)	5 (4,753)	189 (191,738)

The design matrix given in Table 8 is used to specify the column effects model for the $5\ x\ 3$ cross-classification of age and chronic disease status. In the design matrix, the third and fifth columns correspond to the column effects parameters. Note that as the chronic disease status variable has three levels, we define (C-1) column effects parameters.

Table 8. Design matrix for the column effects model

Age	Illnesses	τ_1	τ_2
1	1	1	0
1	2	0	1
1	3	-1	-1
2	1	2	0
2	2	0	2
2	3	-2	-2
3	1	3	0
3	2	0	3
3	3	-3	-3
4	1	4	0
4	2	0	4
4	3	-4	-4
5	1	5	0
5	2	0	5
5	3	-5	-5

Table 9. The goodness of fit statistics, degrees of freedom and p-value of model

Model	G^2	df	p-value
Column effects	4.39	6	0.624

As seen in Table 9, the column effects model holds true for the China data set with G^2 =4.39 and 6 degrees of freedom. Hence, the model equation is,

$$\log(E_{ij}) = 2.502 + 0.087CE1 - 0.638CE2 + 0.551CE3 - 6.001age1 - 1.897age2 - 0.38age3 - 0.469age4 + 8.747age5 + 3.186illnesses1 + 2.246illnesses2 - 5.426illnesses3 .$$

Parameter estimates pertaining the column effects are obtained with their standard errors under the column effects model are given in Table 10.

How the odds ratios are calculated over the expected frequencies is shown in Table 11. The last parameter (τ_3) is estimated so that its total is the sum to zero.

The odds ratio, for instance for *i*=1and *j*=1:

$\theta_{11} = Exp(\tau_2 - \tau_1) = Exp(-0.638 - 0.087)$=0.48 (1/0.48=2.06). They can be reversed to provide more meaningful interpretations, with reference to the odds ratios are smaller than "1".

Table 10. Parameter estimations and odds ratios for column effects model

Parameter	Estimation	St. Error	Z	Odds ratio
τ_1	0.087	0.073	1.195	2.06
τ_2	-0.638	0.134	-4765	3.28
τ_3	0.551	0.56	0.98	1.59

The odds ratio can be calculated by using the ML fitted values that satisfy column effects model, given as follows. These values show that the odds that an observation will fall in the *ith* row rather than in *i*+1th row, given that it is in column *j*. For example, as the age groups tend to increase, the death risk of a patient with chronic disease increases 2.06 times more likely than patients without chronic disease. Similarly, as the age groups tend to increase, the death risk of a patient without chronic disease increases 3.28 times more likely than patients with underlying disease unknown and, the death risk of a patient without chronic disease increases 1,59 times more likely than patients with underlying disease unknown.

Table 11. Age groups comparison in terms of their odds ratios

Compared age groups	Odds ratio
0-17 and 18-44	$\hat{\theta}_1 = \frac{E_{11}\times E_{22}}{E_{12}\times E_{21}} = \frac{0.797\times 4.831}{0.151\times 52.659} = 0.484 \rightarrow \frac{1}{0.484} = 2.06$
18-44 and 45-64	$\hat{\theta}_2 = \frac{E_{21}\times E_{32}}{E_{22}\times E_{31}} = \frac{52.659\times 11.638}{4.831\times 261.799} = 0.484 \rightarrow \frac{1}{0.484} = 2.06$
45-64 and 65-74	$\hat{\theta}_3 = \frac{E_{31}\times E_{42}}{E_{32}\times E_{41}} = \frac{261.799\times 5.626}{11.638\times 261.236} = 0.484 \rightarrow \frac{1}{0.484} = 2.06$
65-74 and 75+	$\hat{\theta}_4 = \frac{E_{41}\times E_{52}}{E_{42}\times E_{51}} = \frac{261.236\times 4.753}{5.626\times 455.508} = 0.484 \rightarrow \frac{1}{0.484} = 2.06$

Conclusions

There are several advantages of utilizing efficiently the special models which use the ordinal information. Such models are more parsimonious and have simpler interpretations than the standard models for nominal variables. If at least one of the variables in a two or higher dimensional contingency table, we'd rather some order restricted models. In the fact that researchers prefer to use more conventional statistical methods, we show that when an ordering constraint is imposed on the parameter scores in the row effects model or the column effects model and show how to apply these special models to COVID-19 data sets. The main finding of two modeling approaches is to interpret the odds ratios. Analyzing the number of older patients infected positive COVID-19 test according to age and their medical history in the 50-64; 65-79 and over 80 age groups could be a helpful to arrange the hospital and other resources. Although COVID-19 has been reported from every age group, elderly patients seem to more likely to be more susceptible to infection. The row effects model indicates that having a particular medical history such as hypertension, diabetes, coronary heart disease, cerebrovascular disease, and other histories gets more likely to have COVID-19. For instance, a patient having COPD is more likely to have COVID-19 than for those who have other diseases.

Different countries have diversely demographic changes, while lower-income countries with high fertility rates and have a very young population, high-income countries have a large elderly population. In NYC data, the chronic disease status was distributed to age groups starting 0-17 towards ≥75. The column effect model explains that the older the age groups, the greater the risk, whereas the odds ratio < 1 indicates a decrease in risk in the exposed group. Higher age groups are "odds ratio" times more likely to meet the COVID-19 compared to smaller age groups. The findings suggest that additional care could be required for elderly people with underlying conditions. Researchers from around the world have been

working to figure out more about the epidemiological and clinical characteristics of COVID 19. In this respects, statistical methods allow us to gain valuable insight into the latest COVID-19 data. Fortunately, the downward trend in curve throughout the world suggests that measures as isolation, hand washing, mask-wearing, social distancing are reducing the spread of coronavirus. The lockdown throughout the world and applying the nationwide control measures efficiently prevented an exponential growth in the number of cases. Coronaviruses are a great threat to world health, there is an urgent need to find strong, long-lasting, and virus-specific immune response safe vaccines effective against these agents. Along with the high morbidity and mortality rates of COVID-19 among older adults, İlgili and Kutsal [20] emphasized in their study that after the pandemic, some permanent problems may arise in elderly people.

Conflicts of interest

There are no conflicts of interest in this work.

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