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Modelling Predictors for Usage of facemasks among the students of the Federal Polytechnic Ado-Ekiti, Nigeria

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Abstract

Face cover use by the overall population for restricting the spread of the COVID-19 pandemic has been causing arguments across the globe, however progressively suggested, and the capability of this mediation is not surely known. This paper addressed the use of facemasks among the students of Federal Polytechnic Ado-Ekiti, Nigeria. Three factors investigated to be predictors for use of facemasks in the institution are gender of the students, prior keeping to the rule of social distancing and their various schools or faculties. The log-linear model was employed in order measure the students' tendencies on the use of facemasks and relationship among the variables. Proportional allocation sampling technique was used to carry out the survey on the students from four faculties in the institution. The variable *facemasks* has three ordered levels (always, sometimes, never) upon which frequencies were predicted from the identified variables. Data collected revealed that 47% of the students claimed to always use facemasks while 24% claimed they have never used it. Results revealed that there is a strong relationship between use of facemasks and those who keep social distancing rules and faculties (schools) at 5% level having p-values 3.42e-12 and 0.018 respectively. Results of analysis on three-factor terms shows that model (GFS, GD, FD, DS) having residual deviance value 17.4 on 17 degree of freedom and p = 0.43 gave the closest fitted values to the observed frequencies, and consequently the best model. This suggests that the institution should continue to encourage the students to maintain social distancing in order have reasonable number of them complying with the rule of facemasks usage.

Keywords: Facemasks, log-linear model, residual deviance, three-factor terms.

Introduction

Need for urgent guidance on the use of masks by the people across the globe is required in order to combat the menace of covid-19. Loglinear models display cell counts in contingency tables. They're a little different from other modeling methods in that they don't distinguish between response and explanatory variables. All variables in a loglinear model are essentially "responses" (Agresti (1996). Interpretation of epidemiological data making use of loglinear models, correspondence analysis, many more have been applied in many empirical literature, but the application has not been done on facemasks data (Demssthens et al, 2004).

Brosseau (2009) researched into how masks made of different materials and designs influence their filtering capability. One of the most popular papers mentioning the advantages and dangers of cloth masks is by Macintyre et al (2015). An important way to stop the spread of covid-19 process from occurring is wearing a mask, so it is a source control method (iiswas). According to Dharmadhikari et al (2012) , it was found out that surgical masks decreases transmission of tuberculosis by 0.56 (95%, 33-70%) when used as source control. It was stated by the authors Anfinrud et al (2020), that wearing of faskmasks or mouth covers in public by every person and adherence to significant decrease in the transmission rate of the pandemic. Randomised controlled trials (RCT) findings by Aiello et al (2010) advise that facemasks and hygiene of hands are likely to reduce certain illness, especially respiratory in shared living settings.

The use of masks may be effective in the containment of communicable diseases (Leung et al, 2020), and Eikenberry et al, 2020). Chua et al (2020) reviewed mask wearing from public perspective and technical details of commercial and home made masks. Ordinal variables can be handled by loglinear models (Agresti, 2010) which provide solution for analysis of covid-19 datasets.

An extension of nominal log-models are ordinal loglinear models. Once X and Y norminal variables are examined in a loglinear analysis, the saturated model includes the interaction terms between X and Y. loglinear analysis is also used for analysis of multivariate frequency tables which is gathered by cross-classification of sets of norminal, ordinal or discrete interval level variables (Agresti, 1993, Hagenaars, 1990, and Vermunt, 1997)

Bucca (2020) worked on heatmaps as a visalization technique to convey the complex patterns association captured by loglinear models. Literature establish it that loglinear models are applicable whenever there is no distinction between response and explanatory variables (Agresti, 1993). These models can be applied to contingency tables to reveal possible association patterns between existing variables. In categorical data analysis, contingency tables are one of the most preferred statistical tools based on their interpretability and comprehensibility (Nihan Acar, 2011). In order to measure the adequacy of loglinear models, the goodness of fit statistics such as chi-square (X^2) and deviance (D) may be used. Insight into graphical loglinear models was provided using a concise explanation of the underlying Mathematics and Statistics, also by showing the relationships to conditional independence in probability and graph (Gauraha, 2017). Stutt et al (2020) provided a simple modelling framework to examine the dynamics of covid-19 epidemics when facemasks are worn by the public with or without imposed lock periods.

Tranchet et al (2010) developed a mathematical model that shows the effectiveness of facemask in reducing the spread of Novel Influenza A (HINI). Masks have been suggested as a method for limiting community transmission by asymptomatic or at least clinically undetected carriers (Chan & Yen, 2020), who may be a major driver of transmission of covid-19 (Li et al, 2020). Many mathematical modelling that are highly influential in supplying better comprehension on the mechanism of transmission and challenge of covid-19 pandemic. The mathematical models can be grouped into population based model driven by differential equations (Li et al, 2020; Zhang et al, 2020) and agent-based models (Biswas, Khaleque, and Sen, 2020; Wilder et al, 2020). We are interested in how the cell counts in this table depend on the levels of the categorical variables. If we were interested in modeling, say, marijuana use as a function of alcohol and cigarette use, then we might perform logistic regression. But if we're interested in understanding the relationship between all three variables without one necessarily being the "response", then we might want to try a loglinear model.

2. Methodology

2.1 Loglinear models for two-way and three-way tables

Consider an I by J contingency table that cross-classifies n subjects. When dependent variables are statistically independent, the joint cell probabilities π_{ij} are determined by row and column marginal totals, (Agresti, 2007)

$$\pi_{ij} = \pi_{i+}\pi_{+j}, \quad i = 1,\ldots,I, \qquad j = 1,\ldots,J \tag{1}$$

The cell probabilities π_{ij} are parameters for multinomial distribution. Loglinear model formulas use expected frequencies $\mu_{ij} = n\pi_{ij}$ rather than π_{ij}. Then they apply also to the Poisson distribution for cell counts with expected values μ_{ij}. Under independence, $\mu_{ij} = n\pi_{i+}\pi_{+j}$, for all i and j.

2.2 Loglinear model of independence for two-way table

Represent the row variable by X and the column variable by Y, the condition of independence $\mu_{ij} = n\pi_{i+}\pi_{+j}$, is multiplicative. Taking the log of both sides of the equation produces an additive relation. Namely, log μ_{ij} depends on a term based on the sample size, a term based on the probability in row i, and a term based on the probability in column j. thus, independence takes the form

$$\log \mu_{ij} = \lambda + \lambda_i^X + \lambda_j^Y \tag{2}$$

where λ_i^X and λ_j^Y are row effect and column effect respectively. This model is called the loglinear model of independence. The parameter λ_i^X stands for the effect of classification in row i. The larger the value of λ_i^X, the larger each expected frequency is in row I. In the same vein, λ_j^Y stands for the effect of classification in column j. The null hypothesis of independence is equivalently the hypothesis that this loglinear model holds. The fitted values that satisfy the model are $\hat{\mu}_{ij} = n_{i+}n_{+j}/n$. These are the estimated expected frequencies for the X^2 and G^2 tests of independence, which are also the tests of goodness of fit of the loglinear model.

2.3 Interpretation of parameters in independent model

As equation (1) shows, loglinear models for contingency tables do not distinguish between response and explanatory classification variables. Model (1) treats both X and Y as responses, modeling the cell counts. Loglinear models are examples of generalized linear models. The GLM treats the cell counts as independent observations from some distribution, typically the Poisson. The model regards the observations to be the cell counts rather than the individual classifications of the subjects. Parameter interpretation is simplest when we view one response as a function of

the others. For instance, consider the independence model (1) for $I \times 2$ tables. In row i, the logit for the probability that $Y = 1$ equals

$$\log\left[P(Y=1)/(1-P(Y=1))\right] = \log(\mu_{i1}/\mu_{j2}) = \log \mu_{i1} - \log \mu_{j2}$$

$$= \left(\lambda + \lambda_i^X + \lambda_1^Y\right) - \left(\lambda + \lambda_i^X + \lambda_2^Y\right) = \lambda_1^Y - \lambda_2^Y \tag{3}$$

This logit does not depend on i. That is, the logit for Y does not depend on the level of X. The loglinear model corresponds to the simple model of form, logit[$P(Y = 1)$] = α, whereby the logit takes the same value in every row i. In each row, the odds of response in column 1 equal exp (α) = exp ($\lambda_1^Y - \lambda_2^Y$). In model (2), differences between two parameters for a given variable relate to the log odds of making one response, relative to another, on that variable. For the independence model, one of λ_i^X is redundant, and one of λ_j^Y is redundant. This is analogous to ANOVA and multiple regression models with factors, which require one fewer indicator variable than the number of factor levels. The choice of constraints is arbitrary.

2.4 Saturated model for two-way tables

Variables that are statistically dependent rather than independent satisfy the more complex loglinear model,

$$\log \mu_{ij} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_{ij}^{XY} \tag{4}$$

Where the parameters λ_{ij}^{XY} are association terms that reflect deviations from independence. The parameters stand for interactions between X and Y, whereby the effect of one variable on the expected cell count depends on the level of the other variable. The independence model (2) is the special case in which all $\lambda_{ij}^{XY} = 0$. Direct relationships exist between log odds and the λ_{ij}^{XY} association parameters. For instance, the model for 2 X 2 tables has log odds ratio

$$\log \theta = \log\left(\frac{\mu_{11}\mu_{22}}{\mu_{12}\mu_{21}}\right) = \log \mu_{11} + \log \mu_{22} - \log \mu_{12} - \log \mu_{21}$$
$$= \left(\lambda + \lambda_1^X + \lambda_1^Y + \lambda_{11}^{XY}\right) + \left(\lambda + \lambda_2^X + \lambda_2^Y + \lambda_{22}^{XY}\right) - \left(\lambda + \lambda_1^X + \lambda_2^Y + \lambda_{12}^{XY}\right) - \left(\lambda + \lambda_2^X + \lambda_1^Y + \lambda_{21}^{XY}\right)$$
$$= \lambda_{11}^{XY} + \lambda_{22}^{XY} + \lambda_{12}^{XY} + \lambda_{21}^{XY} \tag{5}$$

Thus, λ_{ij}^{XY} determine the log odds ratio. When these parameters equal zero, the log odds is zero, and X and Y are independent. In $I \times J$ tables, only $(I - 1)(J - 1)$ association parameters are non-redundant. One can specify the parameters so that the ones in the last row and in the last column are zero. These parameters are coefficients of cross-products of $(I - 1)$ indicator variables for X with $(J - 1)$ indicator variables for Y. Tests of independence analyze whether these $(I - 1)(J - 1)$ parameters equal zero, so the tests have residual $df = (I - 1)(J - 1)$.

2.5 Loglinear models for three-way tables

With three-way contingency tables, loglinear models can represent various independence and association patterns. Two-factor association terms describe the conditional odds ratios between variables. For cell expected frequencies

The most general loglinear model for three-way tables is:

$$\log \mu_{ijk} = \lambda + \lambda_i^X + \lambda_j^Y + \lambda_k^Z + \lambda_{ij}^{XY} + \lambda_{ik}^{XZ} + \lambda_{jk}^{YZ} + \lambda_{ijk}^{XYZ} \tag{6}$$

This is the saturated model, it provides a perfect fit

2.6 Loglinear models for higher dimensions

Loglinear models are more complex for three-way tables than for two-way tables, because of the variety of potential association patterns. Basic concepts for models with three-way tables extend readily, however, to multiway tables. We illustrate this for four-way tables, with variables W, X, Y, and Z. Interpretations are simplest when the model has no three-factor terms. Such models are special cases of (WX, WY, WZ, XY, XZ, YZ), which has homogenous associations. Each pair of variables is conditionally associated, with the same odds ratios at each combination of levels of the other two variables. An absence of a two-factor term implies conditional independence for those variables. Model (WX, WY, WZ, XZ, YZ) does not contain an XY term, so it treats X and Y as conditionally independent at each combination of levels of W and Z. A variety of models have three-factor terms. A model could contain WXY, WXZ, WYZ, or XYZ terms. The XYZ term permits the association between any pair of those three variables to vary across levels of the third variable, at each fixed level of W. The saturated model contains all these terms plus a four-factor term.

3. Data, analysis and discussion

The study population for this research is Federal Polytechnic, Ado-Ekiti, Ekiti state, Nigeria. The data used was obtained through a survey conducted among the students of the institution in 2020. Out of 400 copies of structured questionnaires administered on the students, a total of 372 copies were recovered. Proportional allocation method was used in the administration of the questionnaires. The breakdown is as follows: School of Business (SBS) 91, School of Environmental Studies (SES) 96, School of Engineering (SOE) 90, and School of Science and Computer Studies (SSCS) 95.

Table 1: Facemask use data (First 12 rows)

Gender	Socdist	School	Facemasks	Freq
Female	No	SBS	Always	4
Male	No	SBS	Always	5
Female	Yes	SBS	Always	16
Male	Yes	SBS	Always	16
Female	No	SES	Always	3
Male	No	SES	Always	3
Female	Yes	SES	Always	9
Male	Yes	SES	Always	27
Female	No	SOE	Always	2
Male	No	SOE	Always	2
Female	Yes	SOE	Always	25
Male	Yes	SOE	Always	26

The table shows that 27 male students who always use facemasks and keep social distancing rules came from SES

Table 2: Use of facemasks by school (faculties)

	SBS	SES	SOE	SOS
always	41	42	55	35
never	28	22	13	26
sometimes	22	32	22	34

As seen in table 1, students who always used facemask simultaneously has the highest record in SOE and lowest among those who never used it when compared with other schools

Table 3: Use of facemasks by social distancing

	no	yes
always	28	145
never	53	36
sometimes	31	79

Those who use facemasks and keep social distancing has highest frequency, while students who did not use facemasks but keep social distancing sometimes has the least frequency

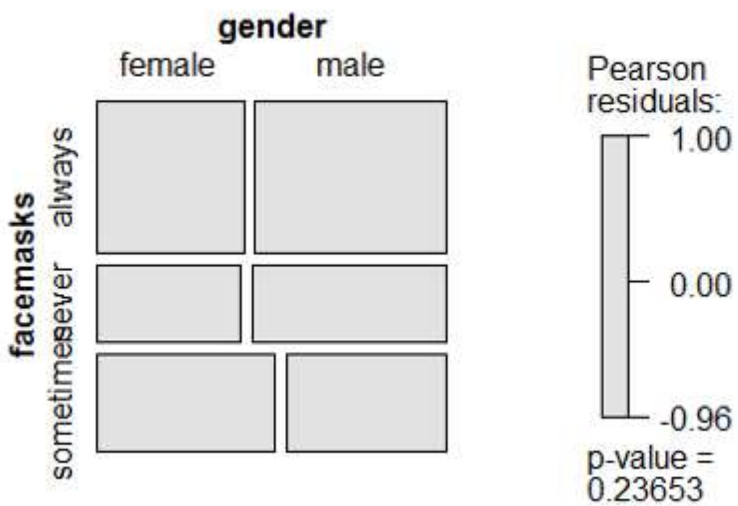

Fig. 1: Mosaic plot showing relationship between gender and use of facemasks

This shows that there is no significant relationship among all the categories of the two variables gender and facemasks. The residuals are so low and the p-values show insignificant relationship between gender and use of facemask

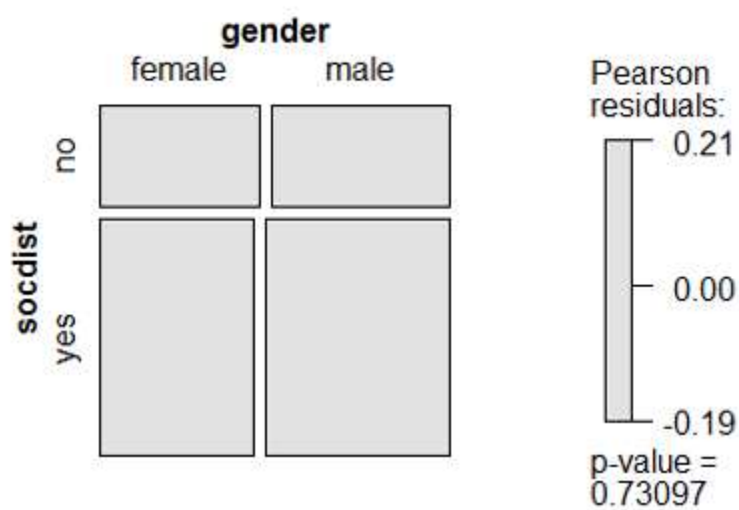

Fig. 2: Mosaic plot showing relationship between gender and keeping social distancing

Compliance to keeping social distancing and gender do not have any relationship

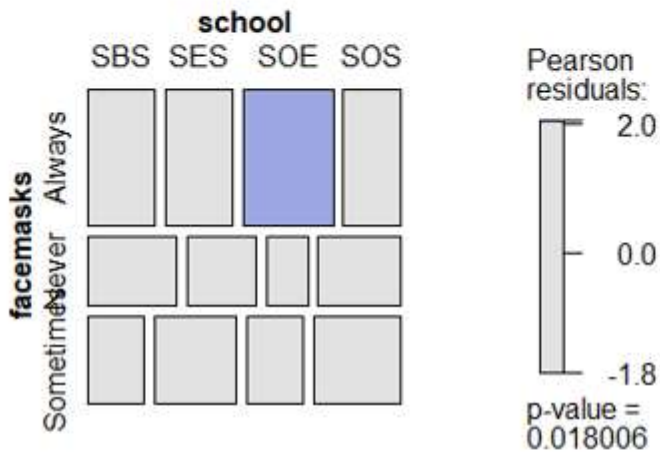

Fig. 3: Relationship between school and use of facemasks

Those who always use facemask came from SOE while students from other schools either used it sometimes or never

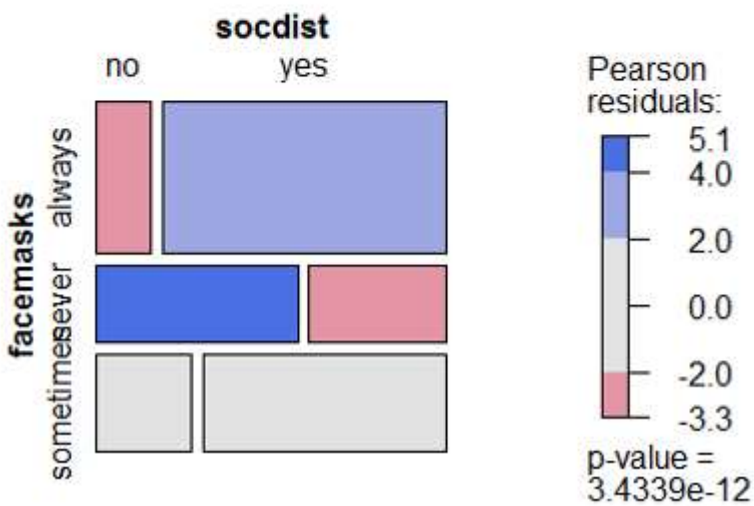

Fig. 4: Relationship between social distancing and use of facemasks

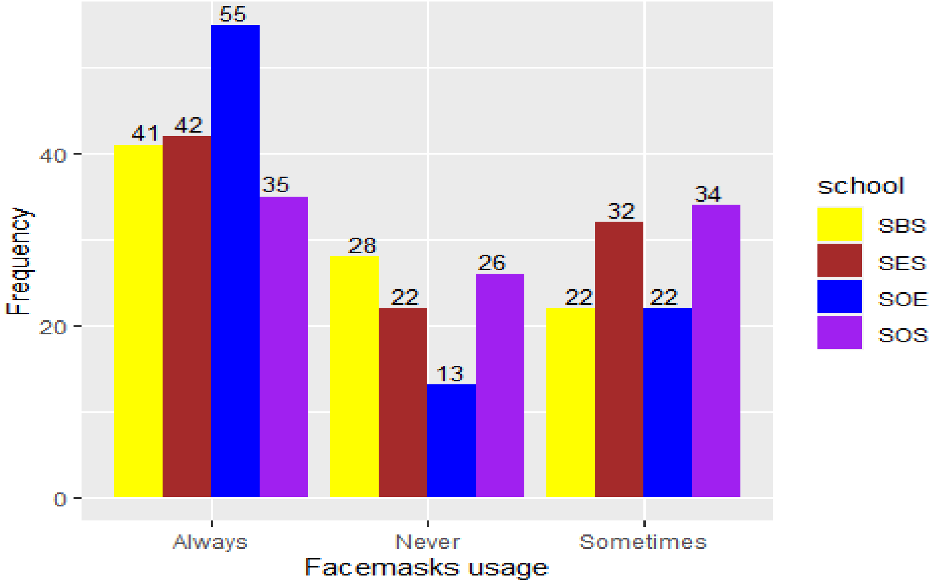

Fig.1: Frequency of facemask usage by school

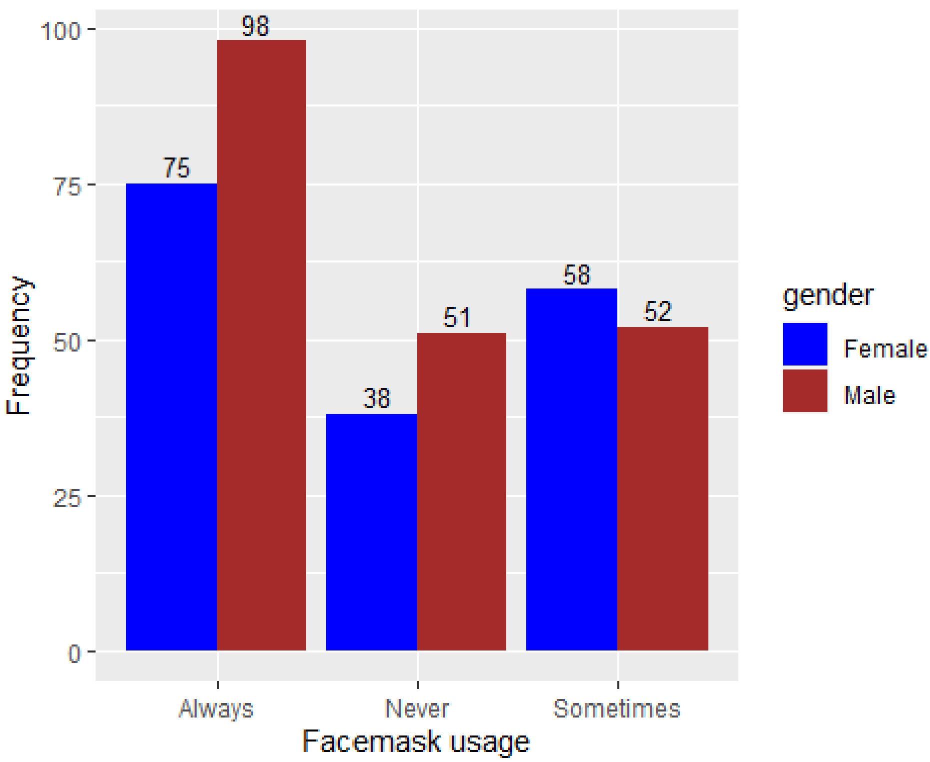

Fig. 2: Observance of social distancing by gender

Table 4: Use of facemasks by schools (faculties) and gender

	Use of facemasks				
	Always (N=173)	**Never (N=89)**	**Sometimes (N=110)**	**Total**	**Test**
School					p-value: 0.0180 (Pearson's Chi-squared test)
SBS	41 (45.05%)	28 (30.77%)	22 (24.18%)	91 (24.46%)	
SES	42 (43.75%)	22 (22.92%)	32 (33.33%)	96 (25.81%)	
SOE	55 (61.11%)	13 (14.44%)	22 (24.44%)	90 (24.19%)	
SOS	35 (36.84%)	26 (27.37%)	34 (35.79%)	95 (25.54%)	
Total	173 (46.51%)	89 (23.92%)	110 (29.57%)	372 (100.00%)	
Gender					p-value: 0.2365 (Pearson's Chi-squared test)
Female	75 (43.86%)	38 (22.22%)	58 (33.92%)	171 (45.97%)	
Male	98 (48.76%)	51 (25.37%)	52 (25.87%)	201 (54.03%)	
Total	173 (46.51%)	89 (23.92%)	110 (29.57%)	372 (100.00%)	

From the table above, it can be seen that there is significant relationship between use of facemasks and their various faculties but not significant with their gender

Table 5: Observance of social distancing by schools (faculties) and gender

	Observance of social distancing			
	No (N=112)	**Yes (N=260)**	**Total**	**Test**
School				p-value: 0.0021 (Pearson's Chi-squared test)
SBS	33 (36.26%)	58 (63.74%)	91 (24.46%)	
SES	24 (25.00%)	72 (75.00%)	96 (25.81%)	
SOE	16 (17.78%)	74 (82.22%)	90 (24.19%)	
SOS	39 (41.05%)	56 (58.95%)	95 (25.54%)	
Total	112 (30.11%)	260 (69.89%)	372 (100.00%)	
Gender				p-value: 0.7310 (Pearson's Chi-squared test)
Female	53 (30.99%)	118 (69.01%)	171 (45.97%)	
Male	59 (29.35%)	142 (70.65%)	201 (54.03%)	
Total	112 (30.11%)	260 (69.89%)	372 (100.00%)	

The table shows that there is significant relationship between observance of social distancing and their various faculties but not significant with the gender of the students

Pearson's Residuals

Pearson's residuals are standardized distances between the observed and the expected responses, and the larger the residuals, the greater the contribution of the cell to the magnitude of the resulting chi-square obtained value

Null deviance and Residual deviance

The null deviance shows how well the response is predicted by the model with nothing but an intercept, while residual deviance shows how well the response is predicted by the model when the predictors are included. If the null deviance is really small, it means that the null model explains the data pretty well, likewise with the residual deviance. The null hypothesis of this test is that the expected frequencies satisfy the given loglinear model.

Structures for loglinear models

The variables in the datasets on use of facemasks among 372 students of Federal Polytechnic, Ado-Ekiti are defined as follows, gender (G), facemasks use (F), keeping social distancing (D), and school (S)

To investigate the complexity of the model needed, we consider model (G, F, D, S) containing only single-factor terms, model (GF, GD, GS, FD, FS, DS) containing also all the two-factor terms, and model (GFD, GFS, GDS, FDS) containing also all the three-factor terms.

Table 4: Estimates for loglinear model (G, F, D, S)

Model	Estimate	Std. Error	P-value
Intercept	1.7676	0.1532	< 2e-16 ***
Gmale	0.1616	0.1040	0.1202
Dyes	0.8421	0.1130	9.24e-14 ***
Sses	0.0534	0.1463	0.7146
Ssoe	-0.0110	0.1486	0.9407
Ssos	0.0430	0.1466	0.7693
Fnever	-0.6646	0.1304	3.48e-07 ***
Fsometimes	-0.4528	0.1219	0.000205 ***

Looking at the model we see three highly significant coefficients and p-values near 0. We tested for the accuracy of the model by comparing the fitted values with the actual values.

Table 5: Fitted values from loglinear model (G, F, D, S)

G	D	S	F	Freq	fitted(mod1)
Female	No	SBS	always	4	5.85
Male	No	SBS	always	5	6.88
Female	Yes	SBS	always	16	13.60
Male	Yes	SBS	always	16	15.98
Female	No	SES	always	3	6.18
Male	No	SES	always	3	7.26
Female	Yes	SES	always	9	14.34
Male	Yes	SES	always	27	16.86
Female	No	SOE	always	2	5.79
Male	No	SOE	always	2	6.81
Female	Yes	SOE	always	25	13.45
Male	Yes	SOE	always	26	15.81

The fitted model is a distance away from the observed data. For instance it can be observed that 25 female students who always used facemasks and kept social distancing come from SOE, but model (G, F, D, S) predicts 13 students. This is a poor fit, we therefore employed other models.

Table 6: Fitted values for Loglinear models (First 12 rows)

Observed	Model1	Model2	Model3	Model4	Model5	Mode16	Mode17
4	5.86	4.87	4.00	4.58	4.08	4.86	5.37
5	6.88	3.29	5.00	3.47	4.04	3.30	3.63
16	13.60	19.02	16.00	19.27	15.92	19.05	18.54
16	15.98	13.82	16.00	13.68	16.96	13.79	13.46
3	6.18	1.80	2.27	1.69	1.65	2.35	1.95
3	7.26	3.73	3.73	3.92	3.87	3.08	4.05
9	14.34	11.28	9.73	11.43	10.35	10.03	11.13
27	16.86	25.20	26.27	24.96	26.13	26.54	24.87
2	5.79	2.71	1.94	2.54	3.02	2.48	1.83
2	6.81	3.22	2.06	3.39	2.94	3.47	2.17
25	13.45	21.54	25.06	21.80	23.98	21.95	22.39
26	15.81	27.53	25.94	27.28	25.06	27.10	28.61

It can be seen that the third and fifth models, that is, models (GFD,GFS,GDS,FDS) and (GFS,GD,FD,DS) respectively are close to the observed data, therefore any of them can be picked as a better fit for prediction. The other models fit poorly. Although, further tests have to be carried out in order to pick the model that actually fit that data best.

Table 7: Goodness of fit tests for Loglinear models relating Facemask use (F), Gender (G), Social distancing (D), and School (S)

Model	Deviance	df	Pvalue
(G,D,S,F)	127.37	40	0.000
(GF,GD,GS,FD,FS,DS)	33.96	23	0.066
(GFD,GFS,GDS,FDS)	9.56	6	0.144
(GFD,GS,FS,DS)	33.64	21	0.040
(GFS,GD,FD,DS)	17.42	17	0.426
(GDS,GF,FD,FS)	31.46	20	0.049
(FDS,GF,GD,GS)	27.36	17	0.053

For the data on students use of facemask, larger deviance values with smaller p-values indicate poorer fits. The models that lack any association term fit poorly, having p-values below 0.05. As a rule of thumb, we will like the residual deviance to be close in value to the degree of freedom. The first model, that is, model (G,D,S,F) has 127.4 on 40 degrees of freedom, this indicates a poor fit. The third model, that is, model (GFS,GD,FD,DS) having deviance value 17.4 on 17 degree of freedom and P = 0.43 which is the highest in the table 7. It says that we have insufficient evidence to reject the null hypothesis that the expected frequencies (fitted values) satisfy our model.

4. Discussion of findings

Three variables identified as predictors for use of facemasks in the institution are gender of the students, keeping to the rule of social distancing and their various schools or faculties. The log-linear model was employed in order measure the students' tendencies on the use of facemasks and relationship among the variables. It can be discovered through the data collected and analysed that 47% of the students claimed to always use facemasks while 24% claimed they have never used it. It is seen that there is a strong relationship between use of facemasks and those who keep social distancing rules and faculties at 5% level having p-values 3.42e-12 and 0.018 respectively. Results of analysis on three-factor terms shows that model (GFS, GD, FD, DS) having residual deviance value 17.4 on 17 degree of freedom and p = 0.43 gave the closest fitted values to the observed frequencies, and consequently the best model as revealed in table. The odds ratios also show high degree of relationship among the four factors.

5. Conclusion and Recommendation

From the various descriptive and inferential statistical analyses carried out and presented in tables and charts, it can be concluded that most of the levels of the categorical variables are significantly related with the use of facemask. Out of the seven models considered, which are models, (G,D,S,F), (GF,GD,GS,FD,FS,DS), (GFD,GFS,GDS,FDS), (GFD,GS,FS,DS), (GFS,GD,FD,DS), (GDS,GF,FD,FS), and (FDS,GF,GD,GS), only model (GFS,GD,FD,DS) fits the data reliably well by having the highest p-value and similar deviance on degree of freedom. Loglinear model is recommended for researchers handling similar data structure that the institution should continue to encourage the students to maintain social distancing in order have reasonable number of them complying with the rule of facemasks usage.

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