

PASSI ANALYSIS

Step by Passi:

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Introduction and curiosities

**PASSI = Progressi delle Aziende Sanitarie per la Salute in Italia
(Progress of Health Authorities for Health in Italy)**

It is a national health surveillance system in Italy that monitors the health behaviors and risk factors of the adults aged 18-69.

A large survey and monitoring program that regularly collects information from people across Italy about things like smoking, physical activity, alcohol use, weight.

This information helps public health authorities make better decisions and create effective programs to improve the health of the population.

The PASSI file used for the project contain approximately 500.000 observations, from the year 2008 to 2020.

We decided to analyze in particular the years 2009 and 2019 to see how the situation has changed during the decade.



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Mental Well-Being



01

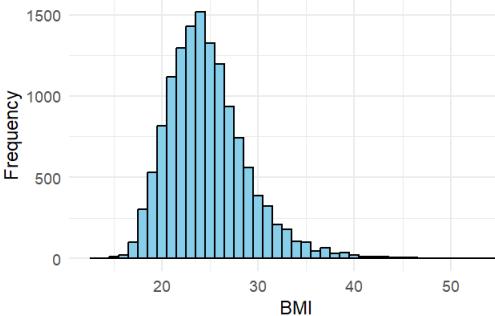
Socioeconomic Variables related to Chronic Diseases



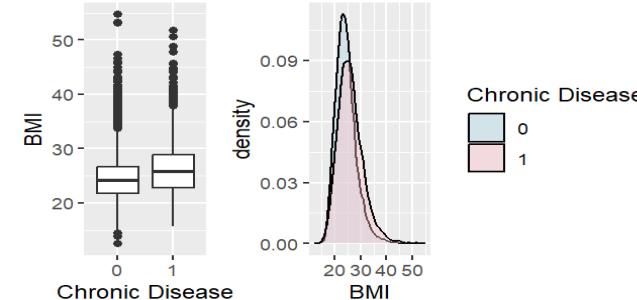
Core Variables

BMI

Distribution of the BMI Variable



BMI Distribution



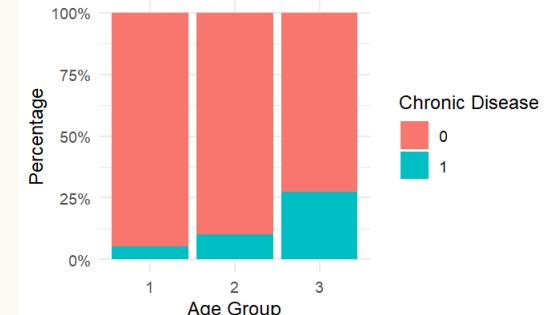
Sex

Percentage Distribution of Chronic Diseases



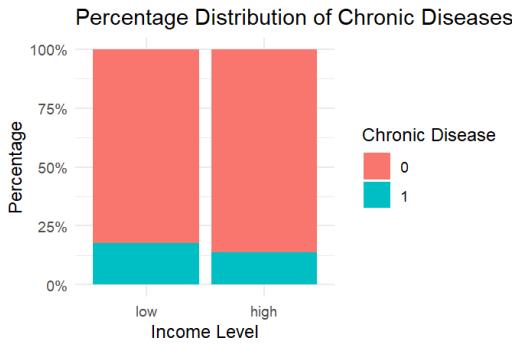
Age Group

Percentage Distribution of Chronic Diseases



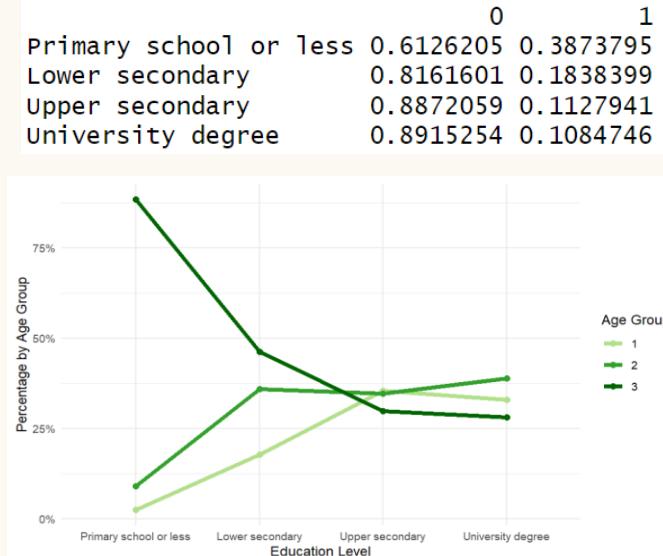
Additional Variables

Income Level

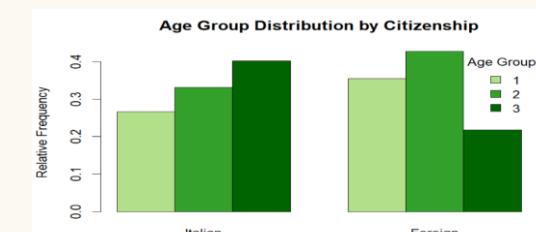
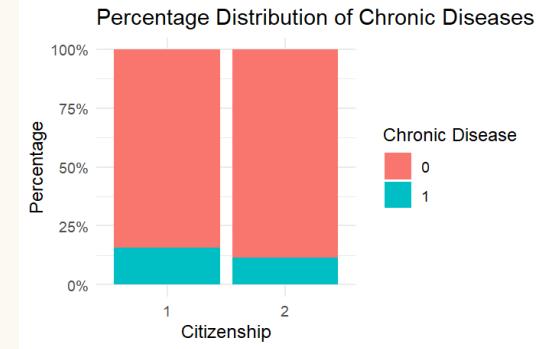


Pearson's Chi-squared test with Yates' continuity correction
data: table(dtpa\$S14_disp_econ_mod, dtpa\$malattiecroniche)
X-squared = 35.071, df = 1, p-value = 3.179e-09

Education Level



Citizenship



Logistic Regression Analysis

$\text{malattiecroniche}_i = \begin{cases} 1 & \text{if the subject has at least one chronic disease} \\ 0 & \text{otherwise} \end{cases}$

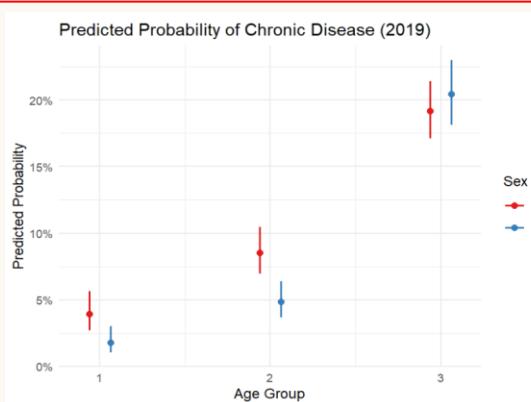
Best Model	2009	2019
BMI	0.04 (4.3%) ***	0.05 (4.9%) ***
Sex	0.08	-0.80 (-55%) *
Age Group 35-49	0.48 (61%) ***	0.80 (122%) ***
Age Group 50-69	1.52 (355%) ***	1.64 (414%) ***
Education Level (LowS, UpS, Uni)	-0.43 -0.67 -0.56 *** (-35% -49% -43%)	-0.54 -0.75 -0.75 *** (-42% -53% -53%)

sesso_intervistatoM	-0.80230	0.33215	-2.415	0.015714	*
sesso_intervistatoM:claeta33	0.91681	0.34872	2.629	0.008561	**

2009

2019

s14_disp_econ_modhigh **



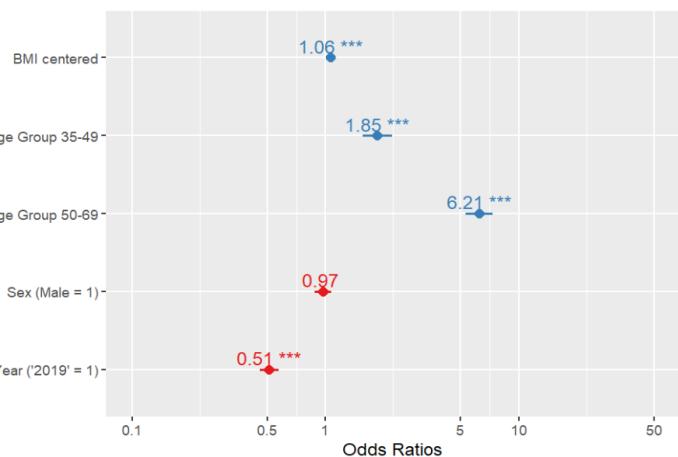
GLMM

Year as fixed effect

ASL as random effect

# Random Effects	
within-Group Variance	3.29 (1.81)
Between-Group Variance	
Random Intercept (as1)	0.03 (0.16)
N (groups per factor)	
as1	209
Observations	13459

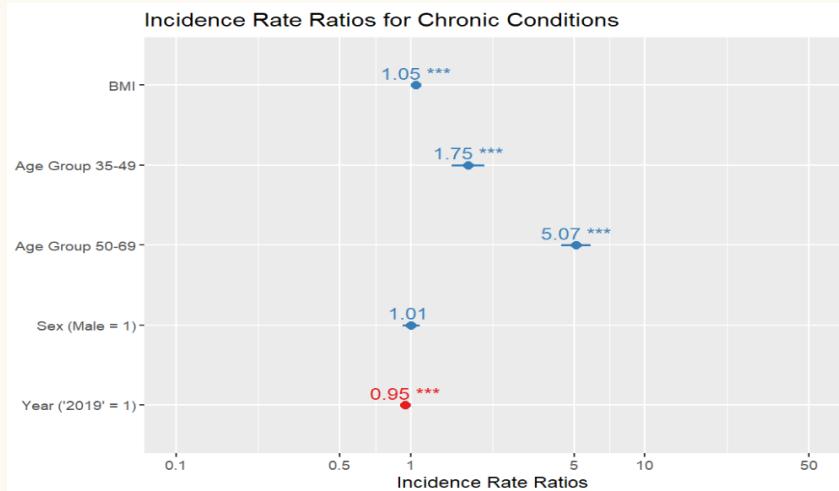
Estimated effects from the GLMM



Count Data Model

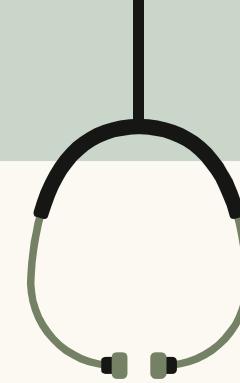
$$Y_i = D_i + R_i + B_i + M_i + T_i$$

$$X_i = \begin{cases} 1 & \text{if individual } i \text{ has the condition} \\ 0 & \text{otherwise} \end{cases}$$





02



Cardiovascular Risk in relation to the quantity of Cigarettes and Alcohol Consumption





Core variables

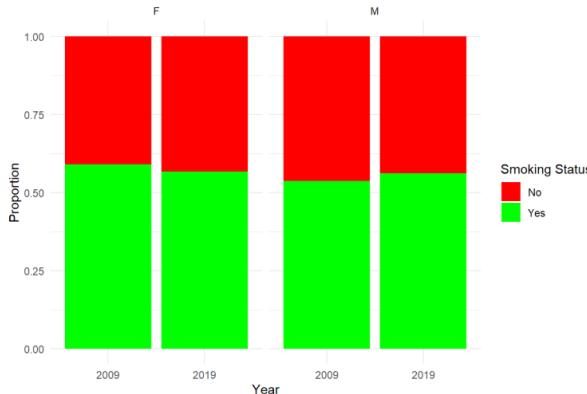
This part of the project focuses on how risk factors, specifically cigarettes and alcohol consumption, can impact cardiovascular risk and, if so, how significantly they impact.

Points of analysis

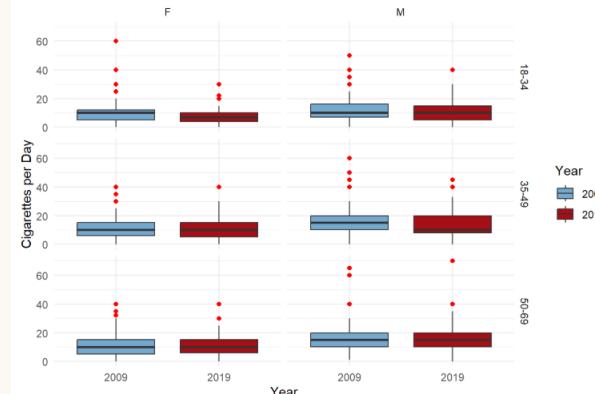
- **Cigarette Consumption:** analysing the smoking status and then, for the smokers, the number of cigarettes smoked per day;
- **Alcohol Consumption:** how many days did the subject drink at least one unit of alcoholic beverage during the last 30 days and, on drinking days, the average quantities of units of alcoholic beverages in a day;
- **Cardiovascular Risk:** how cardiovascular risk varies by sex, year, age class and territorial level (ASL and region);
- **Impact of Cigarettes and Alcohol:** with a Generalized Linear Mixed Model (GLMM) to understand how the factors analysed in the points above are correlated with each other. In particular, analyse whether cigarettes and alcohol can have a significant impact on cardiovascular risk.

Core variables

Proportion of Current Smokers by Year and Sex

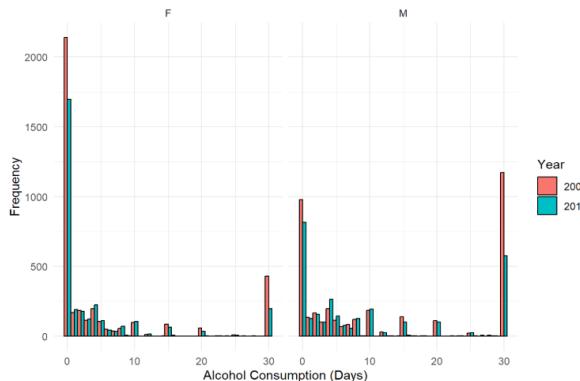


Number of Cigarettes Smoked per Day by Year, Sex and Age Class

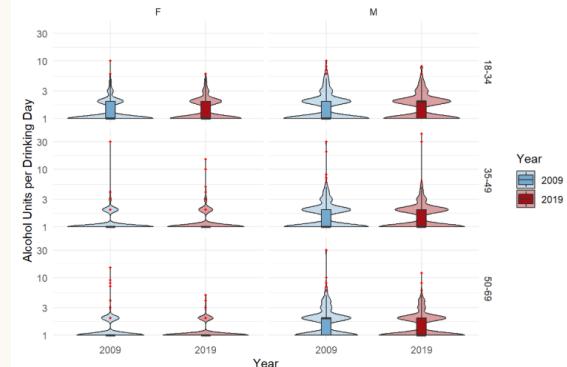


Cigarettes

Alcohol Consumption



Alcohol Units Consumed on Drinking Days by Year, Sex and Age Class



Alcohol

Impact of Cigarettes and Alcohol

```
# Model with ASL as random intercept
Model_Card_ASL = glmer(cardiovasc ~
  as.factor(s03_fumo_att) * as.factor(anno) +
  s05_alcool_gg * as.factor(anno) +
  as.factor(sesso_intervistato) +
  as.factor(claeta3) +
  (1 | asl),
  data = Cigarettes_Alcohol,
  family = binomial,
  control = glmerControl(optimizer = "bobyqa"))

# Model with Region as random intercept
Model_Card_Regione = glmer(cardiovasc ~
  as.factor(s03_fumo_att) * as.factor(anno) +
  s05_alcool_gg * as.factor(anno) +
  as.factor(sesso_intervistato) +
  as.factor(claeta3) +
  (1 | regione),
  data = Cigarettes_Alcohol,
  family = binomial,
  control = glmerControl(optimizer = "bobyqa"))

# Let's compare the two models
anova(Model_Card_ASL, Model_Card_Regione)

parameters:::random_parameters(Model_Card_ASL)
parameters:::random_parameters(Model_Card_Regione)
```



Since the model includes a random intercept for territorial level (ASL or region) we need to see which of the two variables is more significant

```
## Data: Cigarettes_Alcohol
## Models:
## Model_Card_ASL: cardiovasc ~ as.factor(s03_fumo_att) * as.factor(anno) + s05_alcool_gg * as.factor(anno) + as.factor(sesso_intervistato) + as.factor(claeta3) + (1 | asl)
## Model_Card_Regione: cardiovasc ~ as.factor(s03_fumo_att) * as.factor(anno) + s05_alcool_gg * as.factor(anno) + as.factor(sesso_intervistato) + as.factor(claeta3) + (1 | regione)
##          npar      AIC      BIC logLik -2*log(L)   Chisq DF Pr(>Chisq)
## Model_Card_ASL    10 2425.9 2493.2 -1202.9    2405.9
## Model_Card_Regione 10 2423.7 2491.0 -1201.8    2403.7 2.1892  0

## # Random Effects                      ## # Random Effects
## # Within-Group Variance      3.29 (1.81) ## Within-Group Variance      3.29 (1.81)
## Between-Group Variance       ## Between-Group Variance
## Random Intercept (asl)  0.08 (0.28)  ## Random Intercept (regione) 0.04 (0.21)
## N (groups per factor)        ## N (groups per factor)
## asl                         209      ## regione                  21
## Observations                 6178      ## Observations               6178
```

Values are quite similar but we prefer the Model with Region as random intercept

Impact of Cigarettes and Alcohol

①

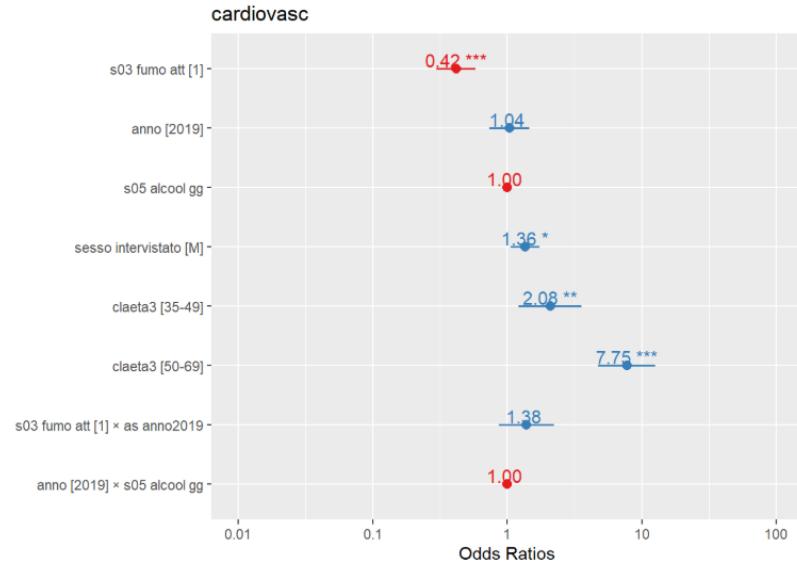
```
## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula:  
## cardiovasc ~ as.factor(s03_fumo_att) * as.factor(anno) + s05_alcool_gg *  
## as.factor(anno) + as.factor(seesso_intervistato) + as.factor(claeta3) +  
## (1 | regione)  
## Data: Cigarettes_Alcohol  
## Control: glmerControl(optimizer = "bobyqa")  
##  
##      AIC      BIC  logLik -2*log(L)  df.resid  
## 2423.7 2491.0 -1201.8   2403.7     6168  
##  
## Scaled residuals:  
##    Min      1Q  Median      3Q     Max  
## -0.4777 -0.2926 -0.1758 -0.1170 12.8731  
##  
## Random effects:  
## Groups Name      Variance Std.Dev.  
## regione (Intercept) 0.0435  0.2086  
## Number of obs: 6178, groups: regione, 21  
##
```

②

```
## Fixed effects:  
##  
## (Intercept)          4.064944  0.276784 -14.686  
## as.factor(s03_fumo_att)1 -0.876969  0.171099 -5.125  
## as.factor(anno)2019    0.035602  0.174057  0.205  
## s05_alcool_gg        -0.002641  0.005924 -0.446  
## as.factor(seesso_intervistato)M 0.306223  0.125360  2.443  
## as.factor(claeta3)35-49 0.733750  0.273961  2.678  
## as.factor(claeta3)50-69 2.047800  0.249195  8.218  
## as.factor(s03_fumo_att)1:as.factor(anno)2019 0.324744  0.241177  1.346  
## as.factor(anno)2019:s05_alcool_gg -0.004570  0.009085 -0.503  
##  
## (Intercept) < 2e-16 ***  
## as.factor(s03_fumo_att)1 2.97e-07 ***  
## as.factor(anno)2019 0.8379  
## s05_alcool_gg 0.6558  
## as.factor(seesso_intervistato)M 0.0146 *  
## as.factor(claeta3)35-49 0.0074 **  
## as.factor(claeta3)50-69 < 2e-16 ***  
## as.factor(s03_fumo_att)1:as.factor(anno)2019 0.1781  
## as.factor(anno)2019:s05_alcool_gg 0.6149  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Correlation of Fixed Effects:  
##  
## (Intr) as.(03_)1 as.()2019 s05_1_ a.(_M a.(3)3 a.(3)5 a.(03_)1:  
## as.f(03_)1 -0.297  
## as.fc()2019 -0.283  0.299  
## s05_alcl_gg -0.155  0.013   0.420  
## as.fctr(_M -0.264  0.069   0.017   -0.225  
## as.(3)35-49 -0.753  0.055   -0.014  -0.030  0.006  
## as.(3)50-69 -0.834  0.112   -0.025  -0.065  0.001  0.836  
## a.(03_)1:  0.152  -0.696   -0.492  -0.021 -0.033 -0.005 -0.015  
## a.()2019:05 0.167  -0.026   -0.579  -0.614 -0.002  0.006  0.009  0.036
```



Impact of Cigarettes and Alcohol



Looking at the results of the model:

- **Age classes:** 675% (for 50-69 group) and 108% (for 35-49 group) higher probability of having cardiovascular risk;
- **Interactions:** both for cigarettes and alcohol are not significant;
- **Alcohol:** no correlation between alcohol and cardiovascular risk → it is not statistically significant;
- **Smoking:** very strange situation because it is statistically significant but there is an inverse correlation → smokers are more likely to have a low cardiovascular risk than non-smokers.



New variable: Smoking History

The subject, in his entire life, has smoked at least 100 cigarettes in total?

```
# Generalized Linear Mixed Model with smoking history
Model_Card_Regione_2 = glmer(cardiovasc ~
  as.factor(s03_fumo) * as.factor(anno) +
  s05_alcool_gg * as.factor(anno) +
  as.factor(seesso_intervistato) +
  as.factor(claeta3) +
  (1 | regione),
  data = Cigarettes_Alcohol,
  family = binomial,
  control = glmerControl(optimizer = "bobyqa"))
summary(Model_Card_Regione_2)
```

① ## Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
Family: binomial (logit)
Formula: cardiovasc ~ as.factor(s03_fumo) * as.factor(anno) + s05_alcool_gg *
as.factor(anno) + as.factor(seesso_intervistato) + as.factor(claeta3) +
(1 | regione)
Data: Cigarettes_Alcohol
Control: glmerControl(optimizer = "bobyqa")

AIC BIC logLik -2*log(L) df.resid
4469.1 4544.1 -2224.6 4449.1 13300

Scaled residuals:
Min 1Q Median 3Q Max
-0.4300 -0.2819 -0.1472 -0.1091 13.3617

Random effects:
Groups Name Variance Std.Dev.
regione (Intercept) 0.02825 0.1681
Number of obs: 13310, groups: regione, 21
##

② ## Fixed effects:

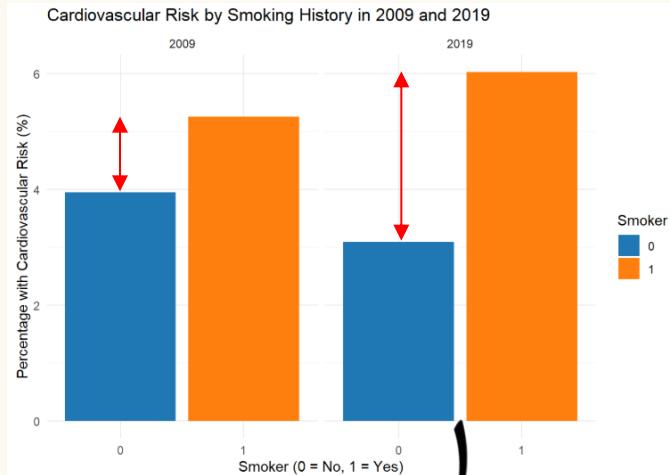
(Intercept) Estimate Std. Error z value Pr(>|z|)
as.factor(s03_fumo)1 0.128320 0.117153 1.095 0.273378
as.factor(anno)2019 -0.317521 0.140117 -2.266 0.023445
s05_alcool_gg -0.002826 0.004564 -0.619 0.535825
as.factor(seesso_intervistato)M 0.323135 0.091256 3.541 0.000399
as.factor(claeta3)35-49 0.703422 0.196111 3.587 0.000335
as.factor(claeta3)50-69 2.266789 0.173045 13.099 < 2e-16
as.factor(s03_fumo)1:as.factor(anno)2019 0.454884 0.175601 2.590 0.009585
as.factor(anno)2019:s05_alcool_gg -0.005931 0.007323 -0.810 0.418016

(Intercept) ***
as.factor(s03_fumo)1
as.factor(anno)2019 *
s05_alcool_gg ***
as.factor(seesso_intervistato)M ***
as.factor(claeta3)35-49 ***
as.factor(claeta3)50-69 ***
as.factor(s03_fumo)1:as.factor(anno)2019 **
as.factor(anno)2019:s05_alcool_gg

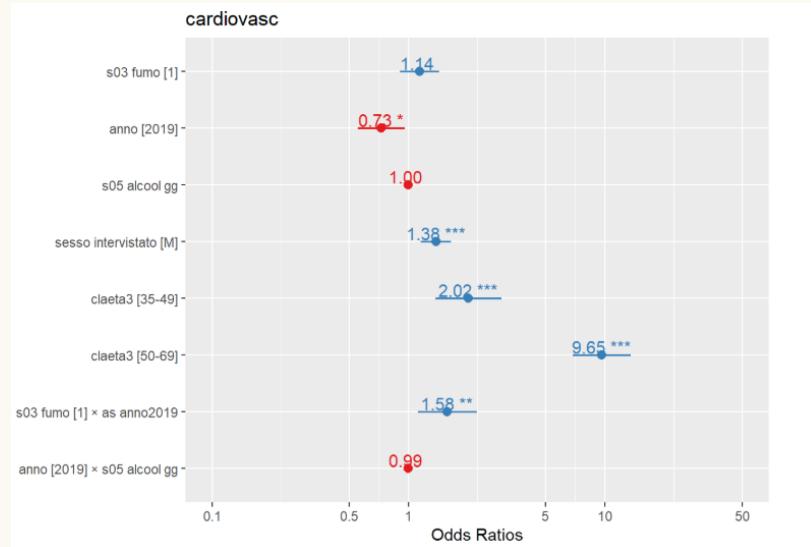
Signif. codes: 0 '***' 0.001 '**' 0.05 '*' 0.1 ' ' 1

Correlation of Fixed Effects:
(Intr) as.(03_)1 as.(.)2019 s05_1_ a.(.)M a.(.)3 a.(.)5 a.(03_)1:
as.fc(03_)1 -0.249
as.fc()2019 -0.301 0.394
s05_alcl_gg -0.092 -0.135 0.259
as.fctr(.)M -0.197 -0.148 -0.028 -0.219
as.(.)35-49 -0.732 -0.004 0.000 -0.036 0.019
as.(.)50-69 -0.820 -0.022 -0.028 -0.078 0.045 0.809
a.(03_)1:(.) 0.192 -0.655 -0.638 0.107 0.022 -0.011 -0.001
a.(.)2019:05 0.111 0.108 -0.341 -0.584 -0.016 0.009 0.011 -0.168

New variable: Smoking History



In 2019 the difference
is more marked



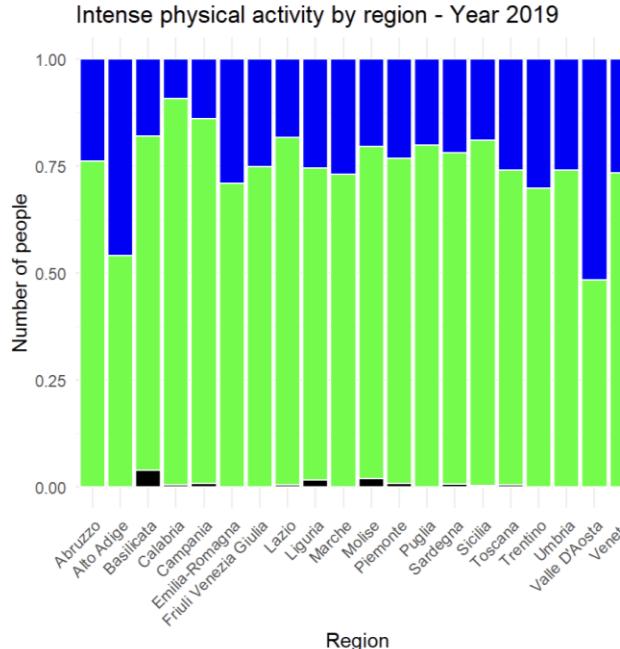
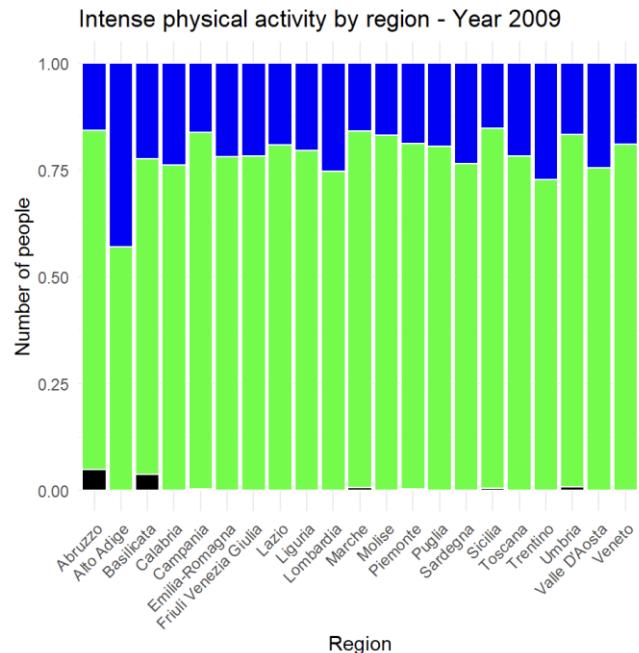
- **The interaction between smoking status and year 2019 is statistically significant.**
- 58% higher cardiovascular risk than non-smokers.
- In 2019 being a smoker significantly increased the probability of having a cardiovascular condition, more than in 2009.

03

Hypertension Conditions related to Physical Activity



Intense Physical Activity Distribution



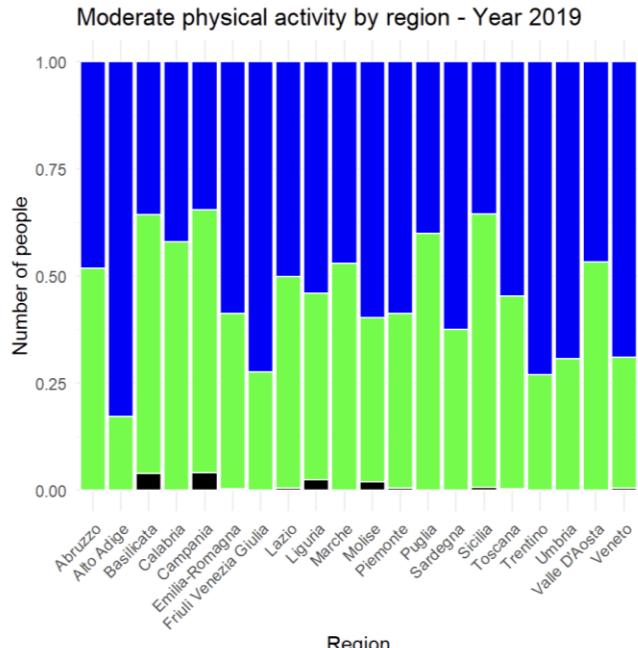
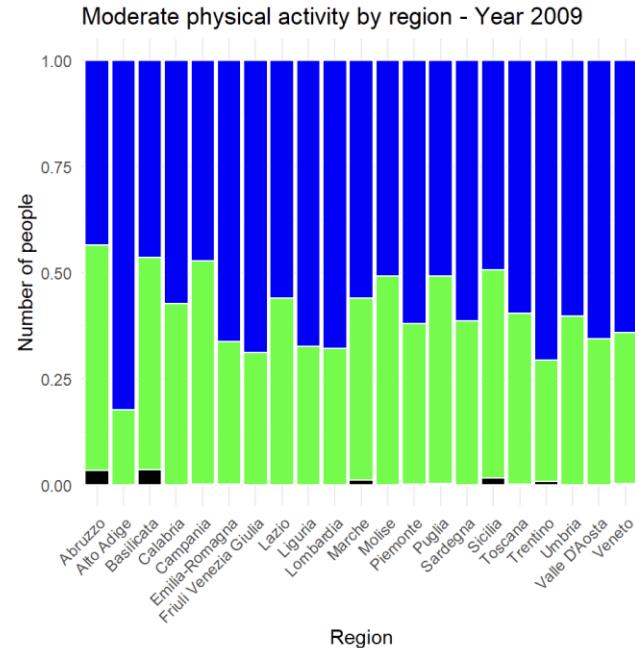
Answers

- Yes (Intense Activity)
- No (No Intense Activity)
- I don't know/I don't remember

```
##   attivita_label           n percentuale
##   <fct>                <int>     <dbl>
## 1 Yes (Intense Activity)    1499    20.1
## 2 No (No Intense Activity)  5938    79.6
## 3 I don't know/I don't remember  22     0.29
```

```
##   attivita_label           n percentuale
##   <fct>                <int>     <dbl>
## 1 Yes (Intense Activity)    1430    23.4
## 2 No (No Intense Activity)  4660    76.2
## 3 I don't know/I don't remember  28     0.46
```

Moderate Physical Activity Distribution



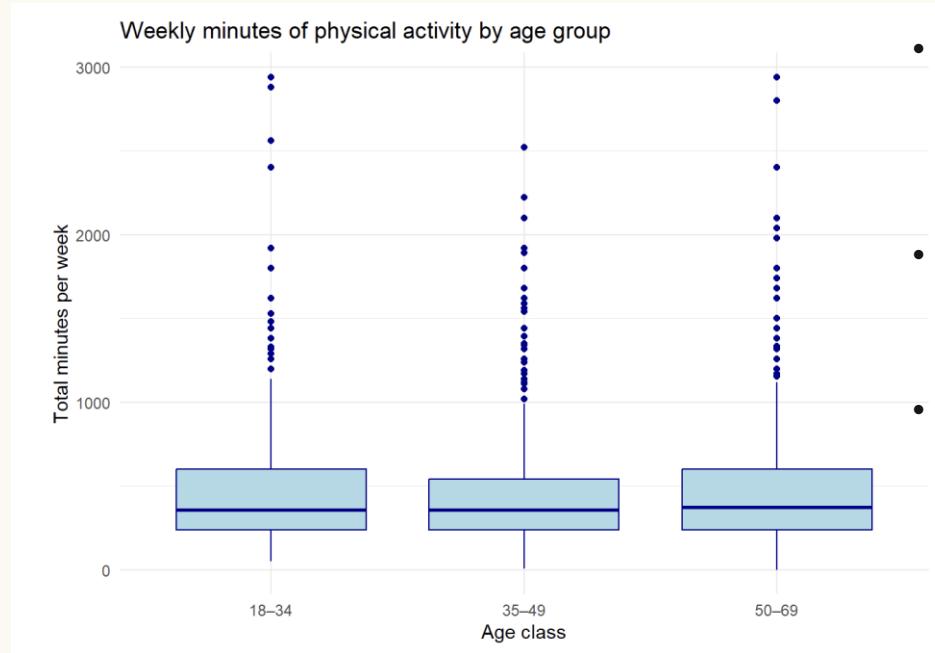
Answers

- Yes (Moderate Activity)
- No (No Moderate Activity)
- I don't know/I don't remember

## attivita_label	n	percentuale
## <fct>	<int>	<dbl>
## 1 Yes (Moderate Activity)	4468	59.9
## 2 No (No Moderate Activity)	2971	39.8
## 3 I don't know/I don't remember	25	0.33

## attivita_label	n	percentuale
## <fct>	<int>	<dbl>
## 1 Yes (Moderate Activity)	3302	54.0
## 2 No (No Moderate Activity)	2774	45.3
## 3 I don't know/I don't remember	43	0.7

Boxplot of Weekly Minutes of Physical Activity



- The median weekly minutes of physical activity is fairly similar across all age groups (18-34, 35-49, 50-69);
- All groups show a wide **interquartile range (IQR)** and long whiskers;
- Every age group has several outliers, with some individuals reporting extremely high levels of weekly activity.

Hypertension and Medical Advice



```
# Filter the responses without including NA values
dataset_contingency = dataset_definitivo %>%
  filter(s07_press_alta %in% c(1, 2),
         s07_sugg_att_fis_press %in% c(1, 2)) %>%
  mutate(
    ipertensione = ifelse(s07_press_alta == 1, "Hypertensive", "No Hypertensive"),
    consiglio_att_fisica = ifelse(s07_sugg_att_fis_press == 1, "Advice Received", "No Advice")
  )

# Absolute frequency table
contingency_table = table(dataset_contingency$ipertensione, dataset_contingency$consiglio_att_fis)
print(contingency_table)
```

```
##          Advice Received No Advice
## Hypertensive      1989       436
```

Contingency table

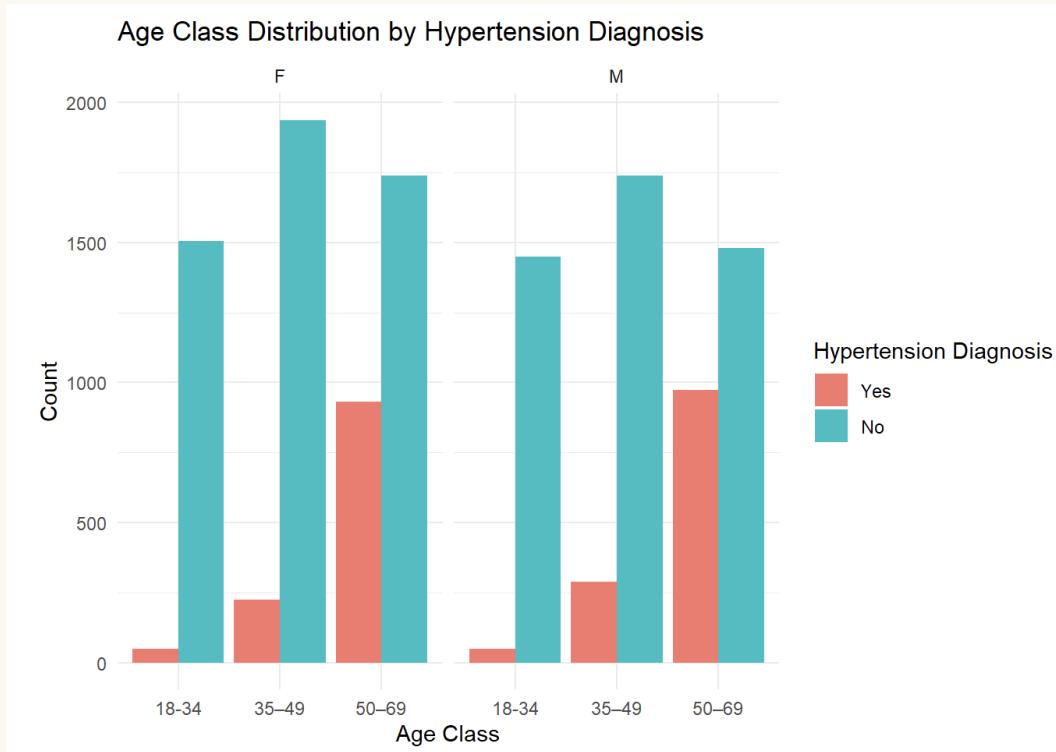
Among those who replied to the survey, 82% of people who was diagnosed with hypertension was also suggested to practice more physical activity.

Hide

```
# Percentages per raw
percentage_table <- prop.table(contingency_table, margin = 1) * 100
print(round(percentage_table, 1))
```

```
##          Advice Received No Advice
## Hypertensive      82        18
```

Hypertension Distribution by Age and Gender



- Hypertension becomes significantly more common with age;
- Women aged 35-49 appear to be less affected than men in the same group.

Generalized Linear Model on Hypertension



```
##  
## Call:  
## glm(formula = s07_press_alta_bin ~ claelta3 + sesso_intervistato,  
##       family = binomial(link = "logit"), data = dataset_filtered_press)  
##  
## Coefficients:  
##                                     Estimate Std. Error z value Pr(>|z|)  
## (Intercept)                 -4.98099   0.11428 -43.587 < 2e-16 ***  
## claelta3                   1.44655   0.04110  35.194 < 2e-16 ***  
## sesso_intervistato1        0.23792   0.04801   4.955 7.22e-07 ***  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## (Dispersion parameter for binomial family taken to be 1)  
##  
##      Null deviance: 12494  on 12366  degrees of freedom  
## Residual deviance: 10722  on 12364  degrees of freedom  
## AIC: 10728  
##  
## Number of Fisher Scoring iterations: 5
```

- The **log-odds** of having high blood pressure for an individual in the **18-34 age group** and for the individual being **female** is **-4.98**, which corresponds to a **very low probability** of hypertension;
- Each older age group is associated with **over four times greater odds** of having blood pressure.

04

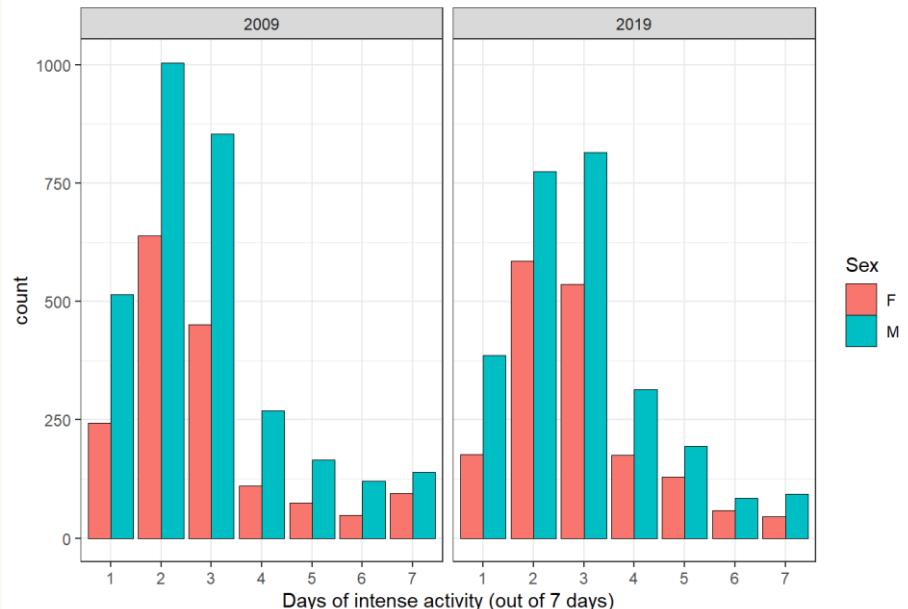
Physical Health in relation to Mental Well-Being



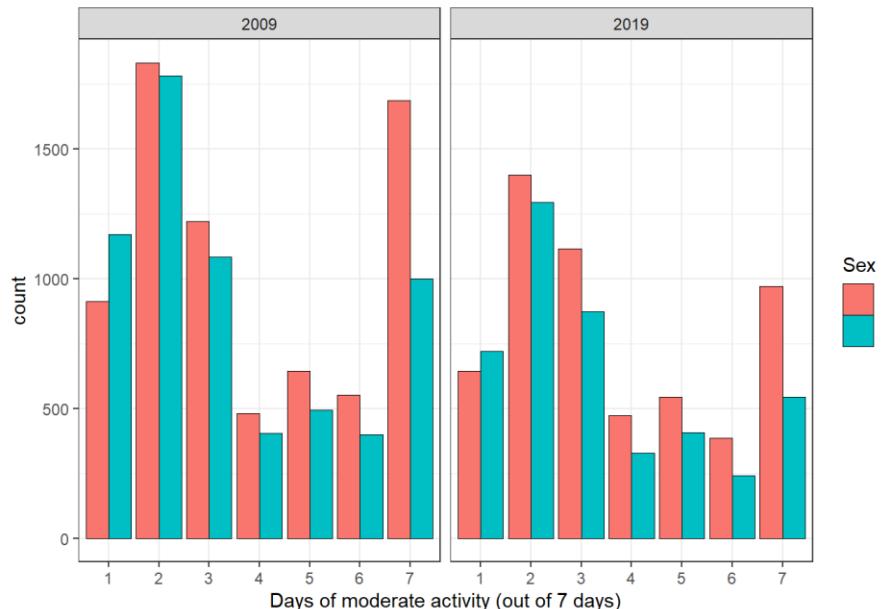
Explorative Analysis

Plots of the distribution of intense and moderate activity in days

Activity distribution by sex and year

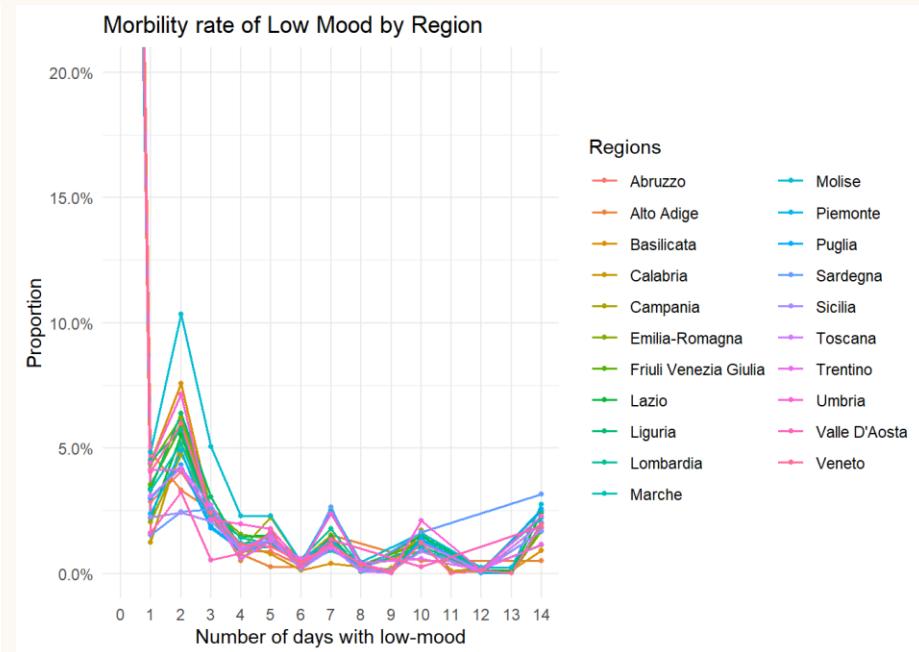
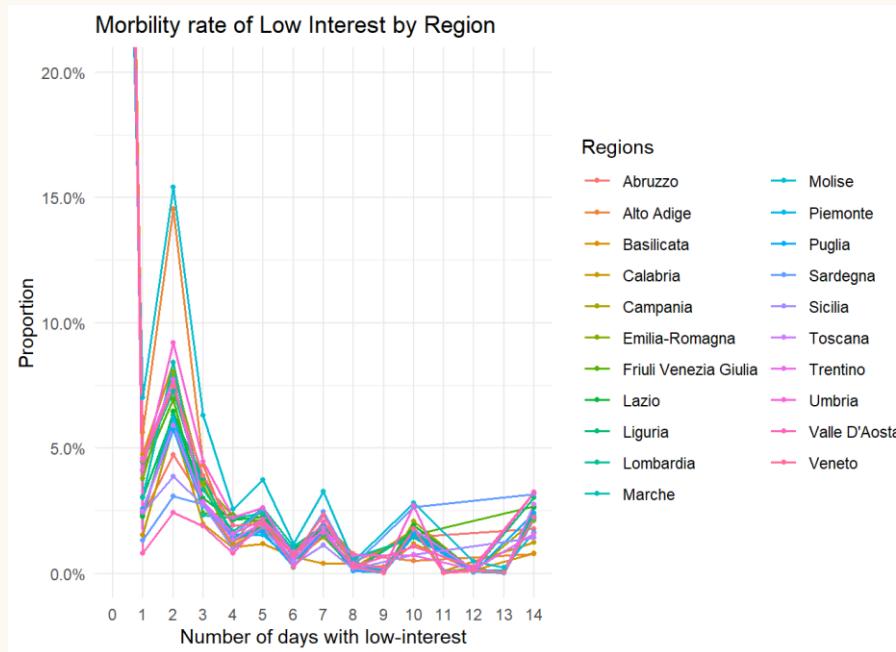


Activity distribution by sex and year



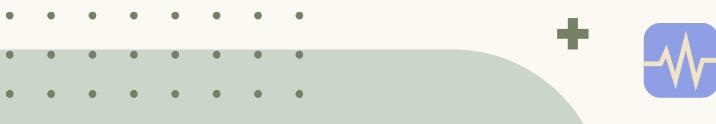
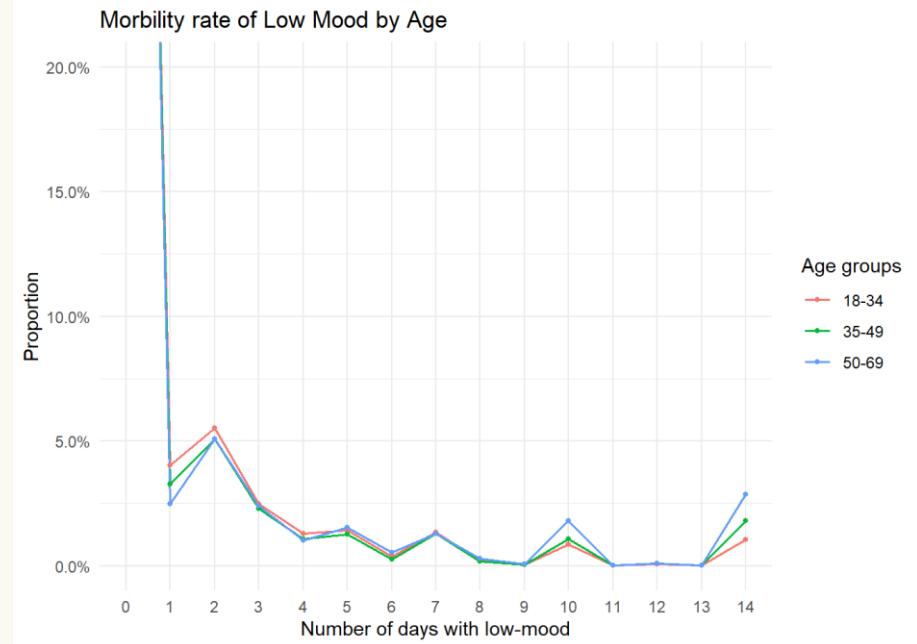
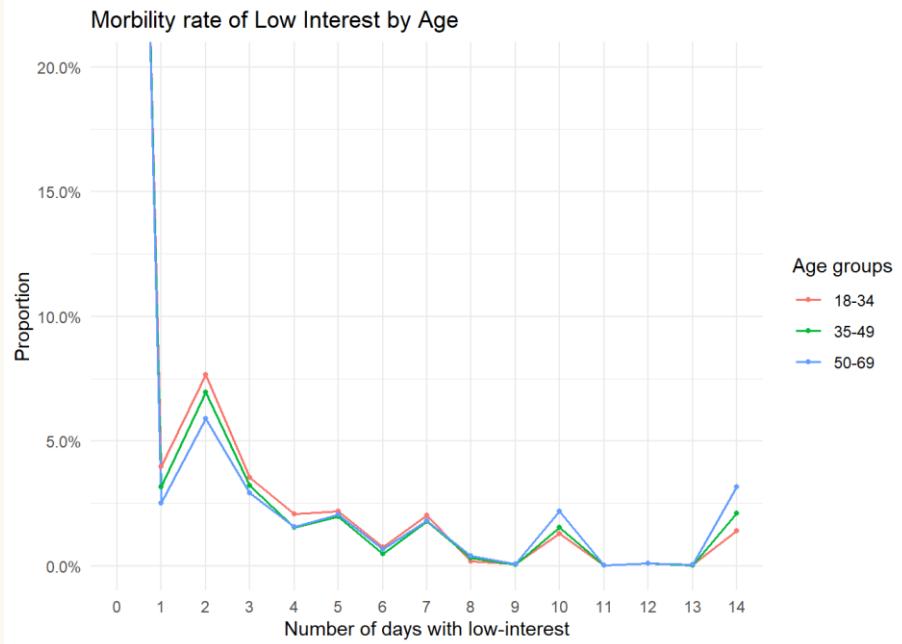
Plots of the proportions/morbidity rates of `s12_poco_inter_gg` and `s12_giu_morale_gg`

- grouping by region and zooming in the interval between 0% and 20% -



Plots of the proportions/morbidity rates of `s12_poco_inter_gg` and `s12_giu_morale_gg`

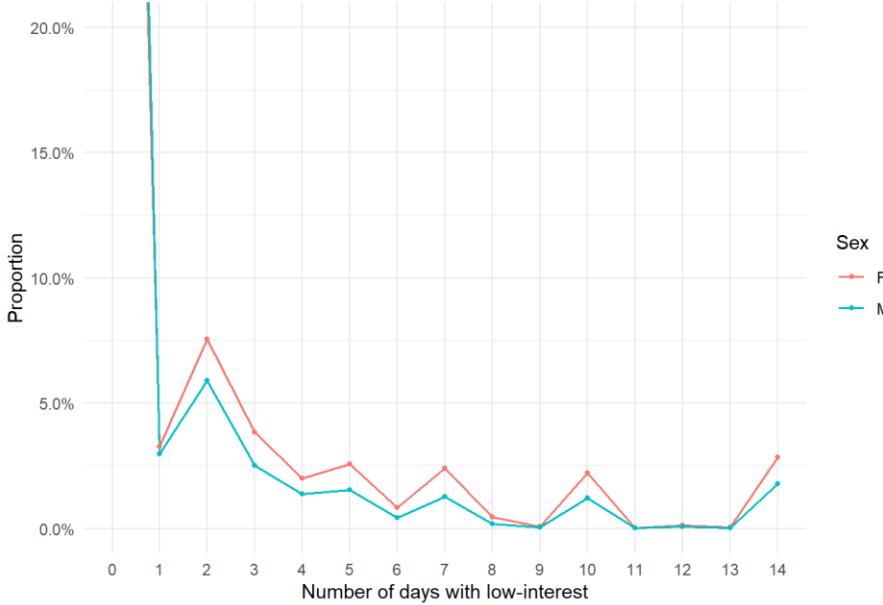
- grouping by age and zooming in the interval between 0% and 20% -



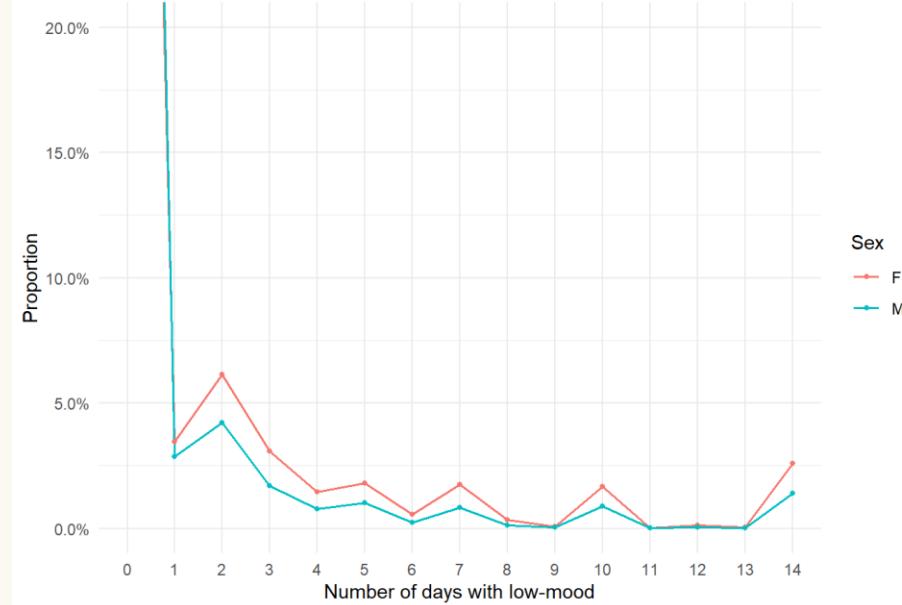
Plots of the proportions/morbidity rates of `s12_poco_inter_gg` and `s12_giu_morale_gg`

- grouping by sex and zooming in the interval between 0% and 20% -

Morbidity rate of Low Interest by Sex



Morbidity rate of Low Mood by Sex





Fitting regression models

With `s12_poco_inter_gg` as dependent variable

Baseline: a female 18–34 year-old with 0 days of moderate or intense activity and without daily fruit consumption.

There is a modest positive correlation (0.24) between `s02_tlib_attiv_inte_gg` and `s02_attiv_moder_gg`, but it isn't very strong. With p-value < 2.2e-16, the null hypothesis (correlation = 0) is rejected with strong evidence, so the correlation is statistically significant and we are 95% confident that the true correlation falls in the range between 0.21 and 0.26.

The interaction of the numerical predictors significantly improves the model's fit and should be considered: it suggests that the association between `s02_attiv_moder_gg` and `s12_poco_inter_gg` varies depending on `s02_tlib_attiv_inte_gg`.

```
## Coefficients:
## (Intercept)          1.256230   0.090309 13.910 < 2e-16
## s02_tlib_attiv_inte_gg -0.091365   0.020332 -4.494 7.00e-06
## s02_attiv_moder_gg    -0.023700   0.013700 -1.730 0.08364
## s04_consumo_frutta1-2 -0.570315   0.071641 -7.961 1.71e-15
## s04_consumo_frutta3-4 -0.780457   0.072764 -10.726 < 2e-16
## s04_consumo_frutta5+ -0.655934   0.080379 -8.160 3.34e-16
## claeta335-49         -0.188928   0.030335 -6.228 4.72e-10
## claeta350-69         -0.388337   0.037701 -10.300 < 2e-16
## sesso_intervistatoM  -0.387415   0.027390 -14.144 < 2e-16
## s02_tlib_attiv_inte_gg:s02_attiv_moder_gg 0.013121   0.004314  3.041 0.00236
##
## (Intercept)          ***
## s02_tlib_attiv_inte_gg ***
## s02_attiv_moder_gg    .
## s04_consumo_frutta1-2 ***
## s04_consumo_frutta3-4 ***
## s04_consumo_frutta5+ ***
## claeta335-49         ***
## claeta350-69         ***
## sesso_intervistatoM ***
## s02_tlib_attiv_inte_gg:s02_attiv_moder_gg **
##
## ---
## Signif. codes:  0 '****' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
## Null deviance: 17492 on 5240 degrees of freedom
## Residual deviance: 17007 on 5231 degrees of freedom
## AIC: 21290
##
## Number of Fisher Scoring iterations: 6
```





Fitting regression models

With `s12_giu_morale_gg` as dependent variable

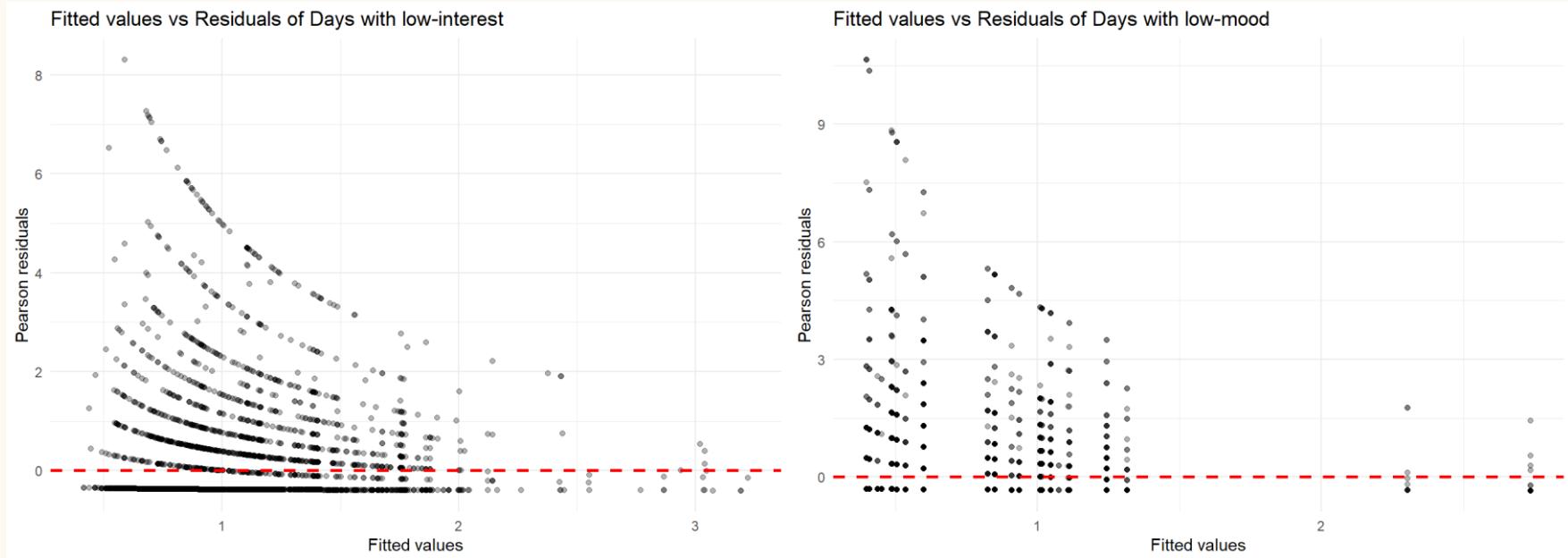
The partial effect of `s02_tlib_attiv_inte_gg` is not statistically significant because p-value = 0.12. Also the partial effect of `s02_attiv_moder_gg` is not statistically significant because p-value = 0.12. Thus, I will take the simpler model with categorical predictors with significant partial effects on the dependent variable.

Poisson distribution has identical mean and variance, but in this case both the models have over-dispersion because alpha>1 (dispersion parameter) with strong statistical evidence(p-value< 2.2e-16).

After fitting Negative Binomial Model there is a drastic reduction in over-dispersion that makes this model more appropriate for inference and confidence intervals.

```
## Call:  
## glm(formula = s12_giu_morale_gg ~ s04_consumo_frutta + clista3 +  
##       sesso_intervistato, family = poisson(link = "log"), data = p  
##       filter(if_all(everything(), ~!is.na(.))))  
##  
## Coefficients:  
##                               Estimate Std. Error z value Pr(>|z|)  
## (Intercept)          0.94258   0.08175 11.530 < 2e-16 ***  
## s04_consumo_frutta1-2 -0.77963   0.08278 -9.418 < 2e-16 ***  
## s04_consumo_frutta3-4 -0.97815   0.08396 -11.650 < 2e-16 ***  
## s04_consumo_frutta5+ -0.03122   0.09253 -8.983 < 2e-16 ***  
## clista335-49        -0.12740   0.03726 -3.419 0.000628 ***  
## clista350-69        -0.13622   0.04339 -3.140 0.001691 **  
## sesso_intervistatoM -0.70597   0.03343 -21.116 < 2e-16 ***  
## ---  
## Signif. codes:  0 '****' 0.001 '***' 0.01 '**' 0.05 '*' 0.1 '.' 1  
##  
## (Dispersion parameter for poisson family taken to be 1)  
##  
## Null deviance: 14388  on 5240  degrees of freedom  
## Residual deviance: 13817  on 5234  degrees of freedom  
## AIC: 16905  
##  
## Number of Fisher Scoring iterations: 6
```

Graphical representations to check the distribution of the residuals



The plots confirm a bit of heteroscedasticity because there is a pattern and points are not randomly spread: residual variability decreases as the fitted values increase. In a count model it's quite normal to have wider residuals where the fitted values are lower or higher because variance increases with the mean.



Thanks for your attention!

Health Data Science
Step by Passi