Preoperative Atelectasis

Part 7: Posthoc Analyses

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Rationale

We observed that SpO2 starts decreasing at BMIs above 40-45. Thus, by having used the WHO obesity class categories, detail on differences above BMI 40 for the extent of atelectasis percentage may have been lost. The WHO obesity class categories do not reflect the extent of variation in BMI observed in this sample of patients:

- Class 1, **BMI [30,35)**: ~25% participants
- Class 2, **BMI [35,40)**: ~25% participants
- Class 3, **BMI >40**: ~50% of participants, with a median BMI above a 5 units range.

Thus, creating subcategories within the class 3 obesity may allow to assess the impact of BMI increases above 40 on atelectasis percentage with more detail.

Thus, I will extend the categories of BMI with the following categories:

- **BMI [30,35)** kg/m^2
- **BMI [35,40)** kg/m^2
- **BMI [40,45)** kg/m^2
- **BMI [44,50)** kg/m^2
- **BMI >50** kg/m^2

Setup

Packages used

```r
if (!require("pacman", quietly = TRUE)) {
  install.packages("pacman")
}


pacman::p_load(
  tidyverse, # Used for basic data handling and visualization.
  table1, #Used to add lables to variables.
  RColorBrewer, #Color palettes for data visualization.
  gridExtra, #Used to arrange multiple ggplots in a grid.
  grid, #Used to arrange multiple ggplots in a grid.
  mgcv, #Used to model non-linear relationships with a general additive model.
  ggmosaic, #Used to create mosaic plots.
  car, #Used assess distribution of continuous variables (stacked Q-Q plots).
  simpleboot, boot, # Used to calculate mean atelectasis coverage and
                    # 95%CI through bootstrapping.
  broom, #Used to exponentiate coefficients of regression models.
  sandwich, #Used to calculate robust standard errors for prevalence ratios.
  EValue, #Used to calculate E-values as sensitivity analysis.
  flextable, #Used to export tables.
  rms, #Used to model ordinal outcome (atelectasis percent) and
       #test proportional odds assumptions.
  VGAM, #Used to model partial proportional odds model.
  gt, #Used to present a summary of the results of regression models.
  report #Used to cite packages used in this session.
)
```

Session and package dependencies

```
R version 4.3.3 (2024-02-29 ucrt)
Platform: x86_64-w64-mingw32/x64 (64-bit)
Running under: Windows 11 x64 (build 22631)

Matrix products: default


locale:
```

```
[1] LC_COLLATE=Spanish_Mexico.utf8  LC_CTYPE=Spanish_Mexico.utf8
[3] LC_MONETARY=Spanish_Mexico.utf8 LC_NUMERIC=C
[5] LC_TIME=Spanish_Mexico.utf8

time zone: Europe/Berlin
tzcode source: internal

attached base packages:
 [1] splines   stats4    grid      stats     graphics  grDevices datasets
 [8] utils     methods   base

other attached packages:
 [1] report_0.5.8       gt_0.10.1          VGAM_1.1-10        rms_6.8-0
 [5] Hmisc_5.1-2        flextable_0.9.5    EValue_4.1.3       sandwich_3.1-0
 [9] broom_1.0.5        boot_1.3-30        simpleboot_1.1-7   car_3.1-2
[13] carData_3.0-5      ggmosaic_0.3.3     mgcv_1.9-1         nlme_3.1-164
[17] gridExtra_2.3      RColorBrewer_1.1-3 table1_1.4.3       lubridate_1.9.3
[21] forcats_1.0.0      stringr_1.5.1      dplyr_1.1.4        purrr_1.0.2
[25] readr_2.1.5        tidyr_1.3.1        tibble_3.2.1       ggplot2_3.5.0
[29] tidyverse_2.0.0    pacman_0.5.1
```

Set seed (for reproducibility of bootstrapping) as the current year 2023:

```r
seed <- 2023
```

Outcome variable

Corroborate that the new BMI breaks category was created successfully:

```
type_obesity
30-35 35-40 40-45 45-50    50
   63    53    57    31    32
```

Percentages:

```
type_obesity
30-35 35-40 40-45 45-50    50
 26.7  22.5  24.2  13.1  13.6
```

Prevalence of atelectasis

```
             Yes    No
frequencies 77.0 159.0
percent     32.6  67.4
```

Prevalence of atelectasis with 95% confidence interval

```
    1-sample proportions test without continuity correction

data:  frequencies, null probability 0.5
X-squared = 28.492, df = 1, p-value = 9.411e-08
alternative hypothesis: true p is not equal to 0.5
95 percent confidence interval:
 0.2696526 0.3884549
sample estimates:
        p
0.3262712
```

The prevalence of atelectasis was **32.6 (95%CI: 26.97, 38.85)**.

Atelectasis - obesity class

Mean expected frequency:

```
  mean_expected_freq
1               23.6
```

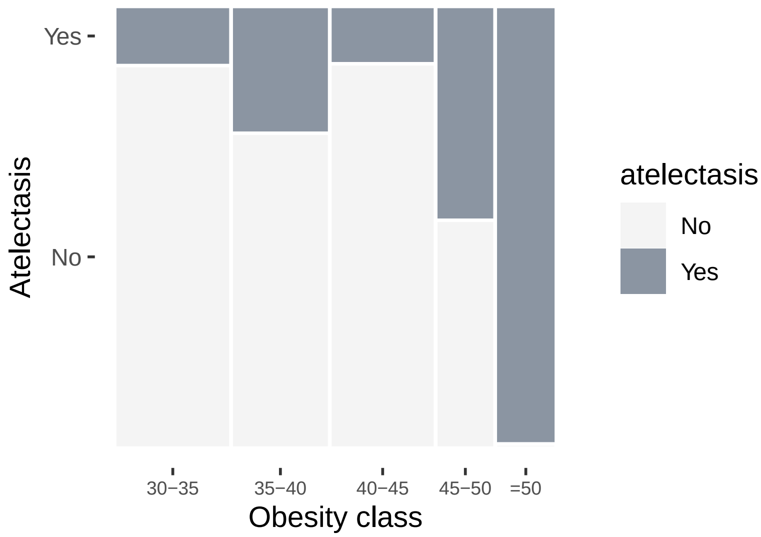
Frequencies:

```
            atelectasis
type_obesity Yes No
       30-35   8 55
       35-40  15 38
       40-45   7 50
       45-50  15 16
        50    32  0
```

Percentage:

```
            atelectasis
type_obesity    Yes     No
       30-35  12.70  87.30
       35-40  28.30  71.70
       40-45  12.28  87.72
       45-50  48.39  51.61
        50   100.00   0.00
```

Mosaic Plot




```
    Pearson's Chi-squared test

data:  frequencies
X-squared = 92.149, df = 4, p-value < 2.2e-16
```

Atelectasis location by obesity class

Mean expected frequency:

```
  mean_expected_freq
1                7.7
```

Mean expected frequency is greater than 5.0, so chi-squared without continuity correction is adequate.

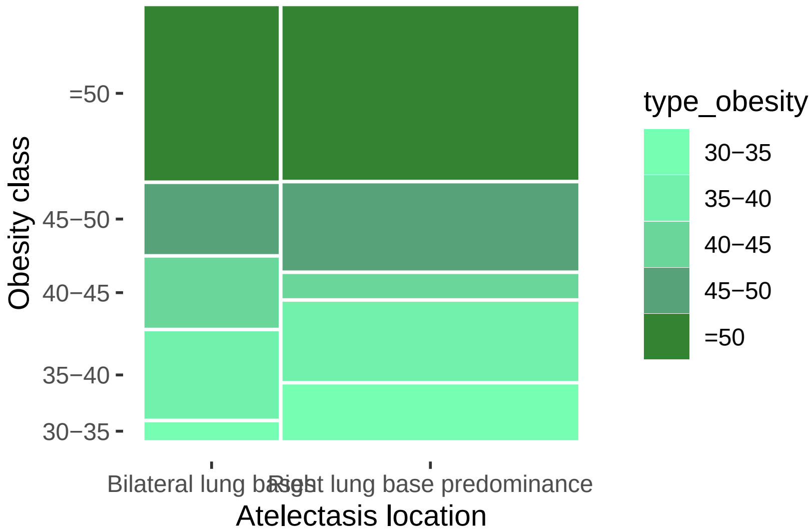
Frequencies:

```
            atelectasis_location
type_obesity Bilateral lung bases Right lung base predominance
       30-35                    1                            7
       35-40                    5                           10
       40-45                    4                            3
       45-50                    4                           11
        50                     10                           22
```

Percentage:

```
           atelectasis_location
type_obesity Bilateral lung bases Right lung base predominance
       30-35                12.50                        87.50
       35-40                33.33                        66.67
       40-45                57.14                        42.86
       45-50                26.67                        73.33
        50                 31.25                        68.75
```

Mosaic Plot




```
    Pearson's Chi-squared test

data:  frequencies
X-squared = 3.6755, df = 4, p-value = 0.4517
```

Prevalence of atelectasis with 95% confidence intervals calculated with sourced script ***Prevalence_atelectasis.R***

atelectasis	type_obesity	n	prev	confint	Bilateral lung bases	Right lung base predominanc
Yes	Total	77	32.63	26.77 - 39.06	24 (31.17%)	53 (68.83%
No	Total	159	67.37		24 (31.17%)	53 (68.83%
Yes	30-35	8	12.70	6.03 - 24.04	1 (12.5%)	7 (87.5%

No	30-35	55	87.30		1 (12.5%)	7 (87.5%
Yes	35-40	15	28.30	17.2 - 42.56	5 (33.33%)	10 (66.67%
No	35-40	38	71.70		5 (33.33%)	10 (66.67%
Yes	40-45	7	12.28	5.49 - 24.29	4 (57.14%)	3 (42.86%
No	40-45	50	87.72		4 (57.14%)	3 (42.86%
Yes	45-50	15	48.39	30.56 - 66.6	4 (26.67%)	11 (73.33%
No	45-50	16	51.61		4 (26.67%)	11 (73.33%
Yes	50	32	100.00	86.66 - 100	10 (31.25%)	22 (68.75%

Atelectasis Percent

Mean atelectasis percentage

The following would be the mean atelectasis percentage coverage if a normal distribution were assumed, which is what has been done in some prior studies:

```
      mean       sd
1 2.658898 4.687145
```

And by obesity class:

```
# A tibble: 5 x 3
  type_obesity   mean    sd
  <fct>         <dbl> <dbl>
1 30-35         0.913  2.89
2 35-40         1.56   3.15
3 40-45         0.702  2.05
4 45-50         3.63   4.22
5  50          10.5    5.40
```

As is evident from these numbers, assuming normality causes standard deviation to capture negative values, which is impossible in reality for this variable.

Thus, bootstrapping the mean and 95%CI is expected to lead to more appropriate estimates.

I will calculate this for class 3 subgroups:

Subgroup 1

Mean:

```
[1] 0.7019737
```

95% CI:

```
BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
Based on 10000 bootstrap replicates

CALL :
boot.ci(boot.out = boot_sub1)

Intervals :
Level      Normal              Basic
95%   ( 0.1755,  1.2276 )   ( 0.1316,  1.1842 )

Level     Percentile            BCa
95%   ( 0.2193,  1.2719 )   ( 0.2193,  1.2719 )
Calculations and Intervals on Original Scale
```

Subgroup 2

Mean:

```
[1] 3.636355
```

95% CI:

```
BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
Based on 10000 bootstrap replicates

CALL :
boot.ci(boot.out = boot_sub2)

Intervals :
Level      Normal              Basic
95%   ( 2.160,  5.084 )   ( 2.097,  5.000 )

Level     Percentile            BCa
95%   ( 2.258,  5.161 )   ( 2.177,  5.081 )
Calculations and Intervals on Original Scale
```

Subgroup 3

Mean:

```
[1] 10.46127
```

95% CI:

```
BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
Based on 10000 bootstrap replicates

CALL :
boot.ci(boot.out = boot_sub3)

Intervals :
Level      Normal              Basic
95%   ( 8.65, 12.31 )   ( 8.52, 12.26 )

Level     Percentile            BCa
95%   ( 8.67, 12.42 )   ( 8.83, 12.50 )
Calculations and Intervals on Original Scale
```

> The mean atelectasis percentage coverage in class 3 obesity subcategories was: subgroup 1 (0.7%, 95%CI:0.22-1.27), subgroup 2 (3.64%, 95%CI:2.18-5.08), and subgroup 3 (10.46%, 95%CI:8.83-12.5).

Atelectasis percentage by obesity subgroups

Now, I will continue assessing atelectasis percentage if assumed to be categorical ordinal:

Mean expected frequency:

```
  mean_expected_freq
1           5.244444
```

Mean expected frequency is very close to 5.0, so I will use chi-squared with continuity correction.

Frequencies:

```
                   type_obesity
atelectasis_percent 30-35 35-40 40-45 45-50  50
               0       55    38    50    16   0
               2.5      2     7     2     0   0
               5        1     2     1     5   5
               7.5      4     4     4     7  14
               10       0     1     0     2   3
               12.5     0     0     0     0   1
               15       0     1     0     1   2
               17.5     1     0     0     0   6
               27.5     0     0     0     0   1

    Pearson's Chi-squared test

data:  frequencies
X-squared = 145.94, df = 32, p-value < 2.2e-16
```

Figure S3

Figure created with sourced script ***FigureS3.R***

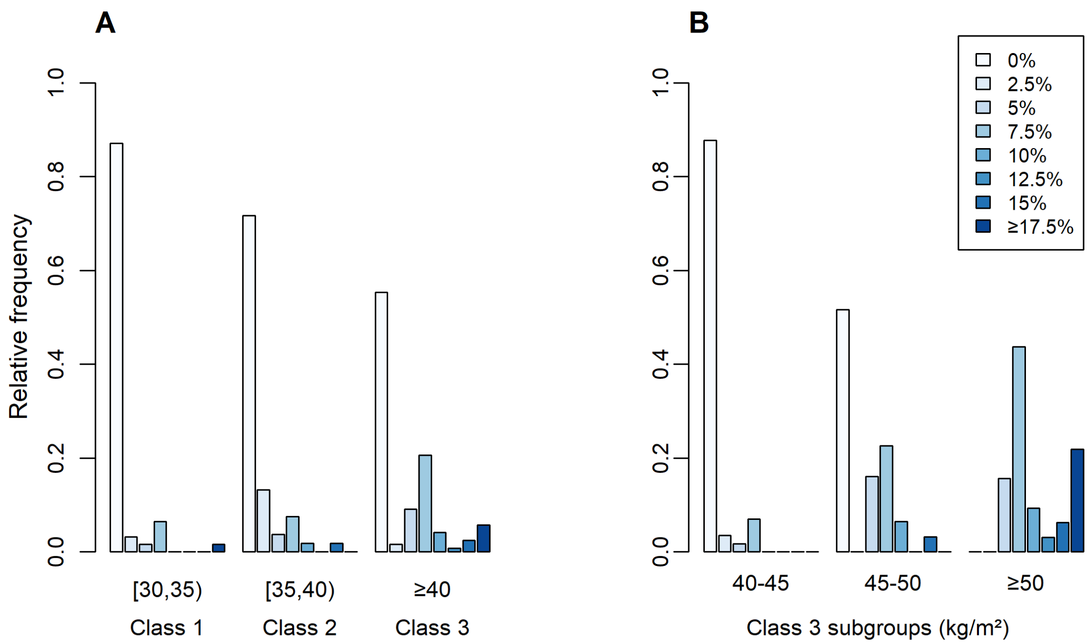


Figure 1: Figure S3. Atelectasis percentage on chest CT by obesity categories.

Prevalence Ratio

This paper and accompanying code were used to calculate prevalence ratios.

A modified Poisson regression model with robust errors will be applied to obtain prevalence ratios.

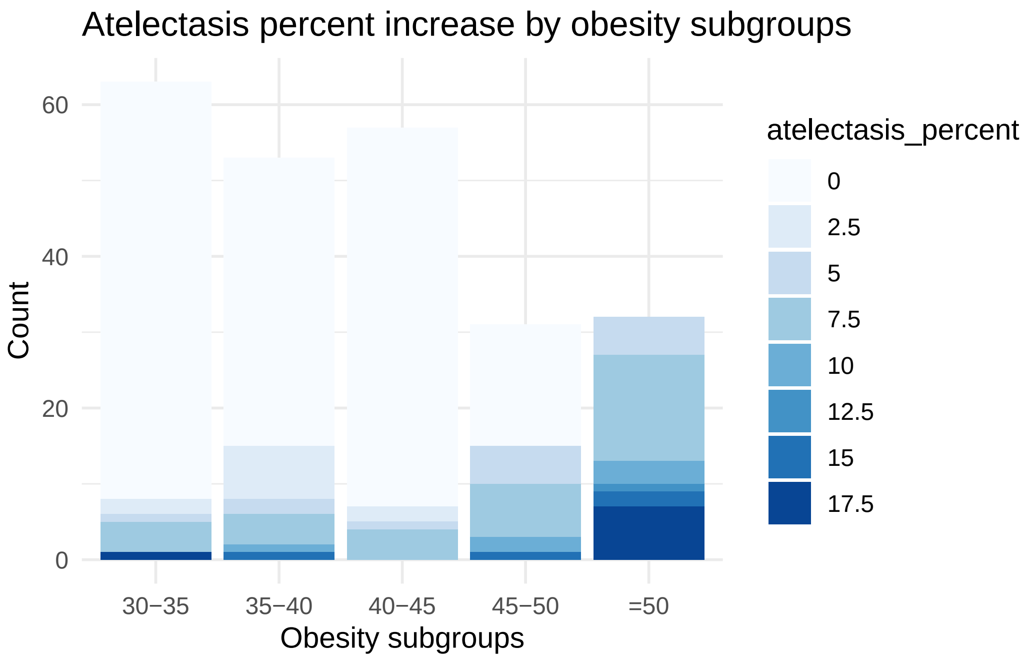
Prevalence ratios were calculated with the accompanying sourced script ***Prevalence_Ratio_subgroups.R***

Table 2 appendage

Category	PR	SE	95%CI	aPR	aSE	a95%CI	Evalue	Evalue_lower
40-45	0.97	0.48	0.37-2.5	0.85	0.46	0.35-2.1	1.63	NA
45-50	3.81	0.38	1.81-8.01	3.52	0.39	1.63-7.61	6.50	2.64
50	7.87	0.33	4.12-15.05	8.00	0.33	4.22-15.17	15.48	7.91

Ordinal Logistic Regression Model

This modelling strategy was performed according to:
- Harrel, Frank. March, 2022. "Assessing the Proportional Odds Assumption and its Impact". Statistical Thinking. March 9, 2022.



Check proportional odds assumption for main variable of interest:

	Model Likelihood Ratio Test	Discrimination Indexes	Rank Discrim. Indexes
Obs 236	LR ^{2} 110.61	R^2 0.416	0.556
Distinct Y 8	d.f. 4	$R^2_{4,236}$ 0.363	
$Y_{0.5}$ 1	Pr(> ^{2}) <0.0001	$R^2_{4,163.1}$ 0.480	
max | log	Score ^{2} 130.41	|Pr(Y	
$L/$ | 3×10^{-7}		median)-½| 0.303	
	Pr(> ^{2}) <0.0001		

		S.E.	Wald Z	Pr(>|Z|)
y 2.5	-1.9013	0.3782	-5.03	<0.0001
y 5	-2.2844	0.3922	-5.82	<0.0001

		S.E.	Wald Z	Pr(>|Z|)
y 7.5	-2.8457	0.4148	-6.86	<0.0001
y 10	-4.6674	0.5112	-9.13	<0.0001
y 12.5	-5.1894	0.5434	-9.55	<0.0001
y 15	-5.2932	0.5508	-9.61	<0.0001
y 17.5	-5.7973	0.5934	-9.77	<0.0001
type_obesity=35-40	0.9189	0.4822	1.91	0.0567
type_obesity=40-45	-0.0551	0.5524	-0.10	0.9205
type_obesity=45-50	2.0158	0.5164	3.90	<0.0001
type_obesity= 50	4.4561	0.5591	7.97	<0.0001

Odds ratio for type obesity in an univariable model:

Effects Response: `atelectasis_percent`	Low	High	Δ	Effect	S.E.	Lower 0.95	Upper 0.95
type_obesity --- 35---40:30---35	1	2		0.91890	0.4822	-0.02626	1.864
Odds Ratio	1	2		2.50600		0.97410	6.449
type_obesity --- 40---45:30---35	1	3		-0.05514	0.5524	-1.13800	1.028
Odds Ratio	1	3		0.94640		0.32050	2.794
type_obesity --- 45---50:30---35	1	4		2.01600	0.5164	1.00400	3.028
Odds Ratio	1	4		7.50700		2.72900	20.650
type_obesity --- 50:30---35	1	5		4.45600	0.5591	3.36000	5.552
Odds Ratio	1	5		86.15000		28.80000	257.800

Proportional odds assumption:

Wald Statistics for `atelectasis_percent`	^{2}	d.f.	P
type_obesity	85.40	4	<0.0001
TOTAL	85.40	4	<0.0001

This shows that the proportional odds assumption is not met since p<0.05 in the ANOVA test.

Will repeat the process described in Part 5:

```
  0   5  10  15 
170  47   7  12 
```

Are subgroups better represented now?

```
    30-35 35-40 40-45 45-50  50
  0    57    45    52    16   0
  5     5     6     5    12  19
  10    0     1     0     2   4
  15    1     1     0     1   9
```

Some improvement.

Will now test the impact of not meeting the proportional odds assumption in a model adjusted for covariates:

```
impact_PO <- impactPO(
  atelectasis_percent ~ type_obesity + age + sex + altitude_cat,
  nonpo = ~ type_obesity,
  data = data,
  newdata = data_prop,
  relax = "multinomial"
  )
```

I was not able to compare against the partial proportional odds (PPO). This can be corroborated by changing `relax = "multinomial"` to `relax = "both"` or `relax = "ppo"` in the above code. This was likely due to a problem in convergence of models with such small subgroups. Previously, I tried comparing models for posthoc analyses in the `VGAM` package and had problems in convergence. Thus, I am presenting the results for the comparison against a multinomial model only:

	PO	Multinomial
Deviance	354.2135	336.7042
d.f.	10	24
AIC	374.2135	384.7042
p	7	21
LR chi^2	109.2016	126.7109
LR - p	102.2016	105.7109
LR chi^2 test for PO		17.50931
d.f.		14
Pr(>chi^2)		0.230051
MCS R2	0.3704304	0.4154487

MCS R2 adj	0.3514770	0.3610492
McFadden R2	0.2356454	0.2734286
McFadden R2 adj	0.2054349	0.1827971
Mean |difference| from PO		0.02990068

The proportional odds model has a lower AIC and higher adjusted McFadden R2, meaning that the proportional odds model is a more parsimonious model that explains the relationship better than a multinomial model.

Thus, I will proceed to fit ordinal models.

Univariate models for covariates:

	Model Likelihood Ratio Test	Discrimination Indexes	Rank Discrim. Indexes
Obs 236	LR ^{2} 58.42	R^2 0.244	0.539
Distinct Y 8	d.f. 1	$R^2{}_{1,236}$ 0.216	
$Y_{0.5}$ 1	Pr(> ^{2}) <0.0001	$R^2{}_{1,163.1}$ 0.297	
max | log $L/$ | 2×10^{-5}	Score ^{2} 70.39	|Pr(Y median)-½| 0.275	
	Pr(> ^{2}) <0.0001		

		S.E.	Wald Z	Pr(>|Z|)
y 2.5	-1.1960	0.1679	-7.12	<0.0001
y 5	-1.4963	0.1824	-8.20	<0.0001
y 7.5	-1.9260	0.2063	-9.34	<0.0001
y 10	-3.4122	0.3139	-10.87	<0.0001
y 12.5	-3.8627	0.3554	-10.87	<0.0001
y 15	-3.9514	0.3648	-10.83	<0.0001
y 17.5	-4.3894	0.4197	-10.46	<0.0001
sleep_apnea=Yes	2.7008	0.3665	7.37	<0.0001

Effects
Response: `atelectasis_percent`

	Low	High	Δ	Effect	S.E.	Lower 0.95	Upper 0.95
sleep_apnea --- Yes:No	1	2		2.701	0.3665	1.982	3.419
Odds Ratio	1	2		14.890		7.260	30.540

Effects Response: `atelectasis_percent`	Low	High	Δ	Effect	S.E.	Lower 0.95	Upper 0.95

<table>
<tr><th></th><th>Model Likelihood
Ratio Test</th><th>Discrimination
Indexes</th><th>Rank Discrim.
Indexes</th></tr>
<tr><td>Obs 236</td><td>LR ^{2} 3.06</td><td>R^2 0.014</td><td>0.104</td></tr>
<tr><td>Distinct Y 8</td><td>d.f. 1</td><td>$R^2_{1,236}$ 0.009</td><td></td></tr>
<tr><td>$Y_{0.5}$ 1</td><td>Pr(> ^{2}) 0.0802</td><td>$R^2_{1,163.1}$ 0.013</td><td></td></tr>
<tr><td>max | log L/ | 0.0001</td><td>Score ^{2} 2.69</td><td>|Pr(Y median)-½| 0.175</td><td></td></tr>
<tr><td></td><td>Pr(> ^{2}) 0.1007</td><td></td><td></td></tr>
</table>

<table>
<tr><th></th><th></th><th>S.E.</th><th>Wald Z</th><th>Pr(>|Z|)</th></tr>
<tr><td>y 2.5</td><td>-0.6588</td><td>0.1430</td><td>-4.61</td><td><0.0001</td></tr>
<tr><td>y 5</td><td>-0.8826</td><td>0.1487</td><td>-5.94</td><td><0.0001</td></tr>
<tr><td>y 7.5</td><td>-1.2022</td><td>0.1602</td><td>-7.50</td><td><0.0001</td></tr>
<tr><td>y 10</td><td>-2.3759</td><td>0.2411</td><td>-9.85</td><td><0.0001</td></tr>
<tr><td>y 12.5</td><td>-2.7833</td><td>0.2868</td><td>-9.70</td><td><0.0001</td></tr>
<tr><td>y 15</td><td>-2.8681</td><td>0.2977</td><td>-9.63</td><td><0.0001</td></tr>
<tr><td>y 17.5</td><td>-3.2923</td><td>0.3608</td><td>-9.12</td><td><0.0001</td></tr>
<tr><td>asthma=Yes</td><td>-1.0153</td><td>0.6414</td><td>-1.58</td><td>0.1135</td></tr>
</table>

Effects Response: `atelectasis_percent`	Low	High	Δ	Effect	S.E.	Lower 0.95	Upper 0.95
asthma --- Yes:No	1	2		-1.0150	0.6414	-2.2720	0.2419
Odds Ratio	1	2		0.3623		0.1031	1.2740

	Model Likelihood Ratio Test	Discrimination Indexes	Rank Discrim. Indexes
Obs 236	LR ^{2} 2.08	R^2 0.010	0.096
Distinct Y 8	d.f. 1	$R^2_{1,236}$ 0.005	
$Y_{0.5}$ 1	Pr(> ^{2}) 0.1490	$R^2_{1,163.1}$ 0.007	

	Model Likelihood Ratio Test	Discrimination Indexes	Rank Discrim. Indexes
max | log $L/$ | 3×10^{-7}	Score 2 2.24 Pr(> 2) 0.1347	|Pr(Y median)-½| 0.173	

		S.E.	Wald Z	Pr(>|Z|)
y 2.5	-0.7883	0.1470	-5.36	<0.0001
y 5	-1.0111	0.1533	-6.60	<0.0001
y 7.5	-1.3318	0.1655	-8.05	<0.0001
y 10	-2.5139	0.2471	-10.17	<0.0001
y 12.5	-2.9216	0.2921	-10.00	<0.0001
y 15	-3.0059	0.3028	-9.93	<0.0001
y 17.5	-3.4289	0.3651	-9.39	<0.0001
sex=Man	0.6380	0.4315	1.48	0.1392

Effects
Response:
`atelectasis_percent`

	Low	High	Δ	Effect	S.E.	Lower 0.95	Upper 0.95
sex --- Man:Woman	1	2		0.638	0.4315	-0.2076	1.484
Odds Ratio	1	2		1.893		0.8125	4.409

	Model Likelihood Ratio Test	Discrimination Indexes	Rank Discrim. Indexes
Obs 236 Distinct Y 8 $Y_{0.5}$ 1 max | log $L/$ | 0.003	LR 2 0.63 d.f. 1 Pr(> 2) 0.4273 Score 2 0.63 Pr(> 2) 0.4274	R^2 0.003 $R^2_{1,236}$ 0.000 $R^2_{1,163.1}$ 0.000 |Pr(Y median)-½| 0.173	0.049

		S.E.	Wald Z	Pr(>|Z|)
y 2.5	-0.2840	0.5705	-0.50	0.6186
y 5	-0.5054	0.5715	-0.88	0.3765
y 7.5	-0.8240	0.5733	-1.44	0.1506

		S.E.	Wald Z	Pr(>$\lvert Z \rvert$)
y 10	-1.9975	0.5986	-3.34	0.0008
y 12.5	-2.4040	0.6188	-3.89	0.0001
y 15	-2.4885	0.6239	-3.99	<0.0001
y 17.5	-2.9121	0.6559	-4.44	<0.0001
age	-0.0110	0.0138	-0.79	0.4278

Effects Response: `atelectasis_percent`	Low	High	Δ	Effect	S.E.	Lower 0.95	Upper 0.95
age	32.75	48.25	15.5	-0.1702	0.2146	-0.5908	0.2504
Odds Ratio	32.75	48.25	15.5	0.8435		0.5539	1.2850

	Model Likelihood Ratio Test	Discrimination Indexes	Rank Discrim. Indexes
Obs 236	LR ^{2} 0.06	R^2 0.000	0.016
Distinct Y 8	d.f. 1	$R^2_{1,236}$ 0.000	
$Y_{0.5}$ 1	Pr(> ^{2}) 0.8060	$R^2_{1,163.1}$ 0.000	
max $\lvert$ log $L/$ $\rvert$ 3×10^{-6}	Score ^{2} 0.06	$\lvert$Pr(Y median)-½$\rvert$ 0.174	
	Pr(> ^{2}) 0.8050		

		S.E.	Wald Z	Pr(>$\lvert Z \rvert$)
y 2.5	-0.7383	0.1491	-4.95	<0.0001
y 5	-0.9595	0.1551	-6.19	<0.0001
y 7.5	-1.2772	0.1667	-7.66	<0.0001
y 10	-2.4491	0.2458	-9.96	<0.0001
y 12.5	-2.8556	0.2906	-9.83	<0.0001
y 15	-2.9401	0.3014	-9.76	<0.0001
y 17.5	-3.3631	0.3638	-9.24	<0.0001
altitude_cat=Moderate	0.0964	0.3906	0.25	0.8051

Effects Response: `atelectasis_percent`	Low	High	Δ	Effect	S.E.	Lower 0.95	Upper 0.95
altitude_cat --- Moderate:Low	1	2		0.09641	0.3906	-0.6692	0.862
Odds Ratio	1	2		1.10100		0.5121	2.368

Multivariable model

	Model Likelihood Ratio Test	Discrimination Indexes	Rank Discrim. Indexes
Obs 236	LR ^{2} 114.10	R^2 0.426	0.562
Distinct Y 8	d.f. 7	$R^2{}_{7,236}$ 0.365	
$Y_{0.5}$ 1	Pr(> ^{2}) <0.0001	$R^2{}_{7,163.1}$ 0.481	
max | log $L/$ | 1×10^{-6}	Score ^{2} 133.56	|Pr(Y median)-½| 0.304	
	Pr(> ^{2}) <0.0001		

		S.E.	Wald Z	Pr(>|Z|)
y 2.5	-2.4485	0.7695	-3.18	0.0015
y 5	-2.8352	0.7786	-3.64	0.0003
y 7.5	-3.4015	0.7916	-4.30	<0.0001
y 10	-5.2495	0.8584	-6.12	<0.0001
y 12.5	-5.7752	0.8830	-6.54	<0.0001
y 15	-5.8795	0.8883	-6.62	<0.0001
y 17.5	-6.3861	0.9152	-6.98	<0.0001
type_obesity=35-40	0.9039	0.4844	1.87	0.0621
type_obesity=40-45	-0.1169	0.5595	-0.21	0.8344
type_obesity=45-50	2.0150	0.5227	3.85	0.0001
type_obesity= 50	4.5168	0.5691	7.94	<0.0001
sex=Man	0.8790	0.4960	1.77	0.0764
age	0.0117	0.0156	0.75	0.4548
altitude_cat=Moderate	-0.0048	0.4607	-0.01	0.9917

Effects Response: atelectasis_percent	Low	High	Δ	Effect	S.E.	Lower 0.95	Upper 0.95
age	32.75	48.25	15.5	0.180700	0.2417	-0.29300	0.6544
Odds Ratio	32.75	48.25	15.5	1.198000		0.74600	1.9240
type_obesity --- 35---40:30---35	1.00	2.00		0.903900	0.4844	-0.04558	1.8530
Odds Ratio	1.00	2.00		2.469000		0.95540	6.3810
type_obesity --- 40---45:30---35	1.00	3.00		-0.116900	0.5595	-1.21400	0.9797
Odds Ratio	1.00	3.00		0.889600		0.29710	2.6640
type_obesity --- 45---50:30---35	1.00	4.00		2.015000	0.5227	0.99050	3.0390
Odds Ratio	1.00	4.00		7.501000		2.69200	20.8900
type_obesity --- 50:30---35	1.00	5.00		4.517000	0.5691	3.40100	5.6320
Odds Ratio	1.00	5.00		91.540000		30.01000	279.3000
sex --- Man:Woman	1.00	2.00		0.879000	0.4960	-0.09320	1.8510
Odds Ratio	1.00	2.00		2.409000		0.91100	6.3680
altitude_cat --- Moderate:Low	1.00	2.00		-0.004817	0.4607	-0.90780	0.8981
Odds Ratio	1.00	2.00		0.995200		0.40340	2.4550

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