Poster Stats

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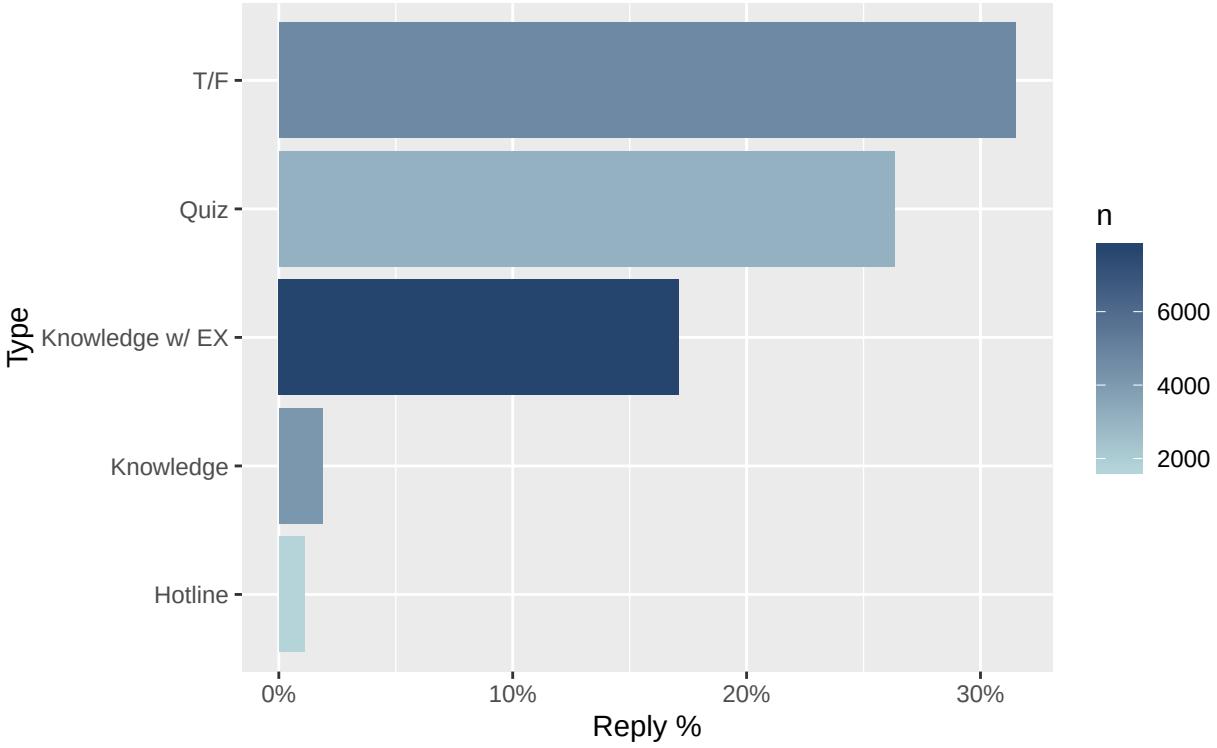
Contents

Graph of response rate to each question type

Here's just an overview of the crude percent of people who responded to each question type:

Type	Yes	No	Reply %	n
Hotline	19	1725	1.1%	1744
Knowledge	78	4082	1.9%	4160
Knowledge w/ EX	1318	6387	17.1%	7705
Quiz	818	2290	26.3%	3108
T/F	1482	3222	31.5%	4704



Chi-Squared

TODO: Effect size..?

Contengency table

Contengency table of responded (yes, no) vs the type of question

	Hotline	Knowledge	Knowledge w/ EX	Quiz	T/F
Yes	19	78	1318	818	1482
No	1725	4082	6387	2290	3222

Test Results

Here's the test results

```
chisq.test(conTable)
##
##  Pearson's Chi-squared test
##
## data:  conTable
## X-squared = 1848.9, df = 4, p-value < 2.2e-16
chisq.test(conTable, simulate.p.value = TRUE, B = 10000)
##
##  Pearson's Chi-squared test with simulated p-value (based on 10000
```

```
##  replicates)
##
## data:  conTable
## X-squared = 1848.9, df = NA, p-value = 9.999e-05
```

Residuals

	Hotline	Knowledge	Knowledge w/ EX	Quiz	T/F
Yes	-16.30	-23.96	-0.50	12.02	23.32
No	7.47	10.97	0.23	-5.50	-10.68

Post-hoc analysis

Using Fisher's Exact. Agrees nicely with the results from the logistic regression (next section)

```
## Adjusted p-values used the bonferroni method.
```

comparison	raw.p	adj.p
Hotline vs. Knowledge	0.03254	0.3254
Hotline vs. Knowledge w/ EX	0	0
Hotline vs. Quiz	0	0
Hotline vs. T/F	0	0
Knowledge vs. Knowledge w/ EX	0	0
Knowledge vs. Quiz	0	0
Knowledge vs. T/F	0	0
Knowledge w/ EX vs. Quiz	0	0
Knowledge w/ EX vs. T/F	0	0
Quiz vs. T/F	8.6e-07	8.57e-06

```
## Adjusted p-values used the fdr method.
```

comparison	raw.p	adj.p
Hotline vs. Knowledge	0.03254	0.03254
Hotline vs. Knowledge w/ EX	0	0
Hotline vs. Quiz	0	0
Hotline vs. T/F	0	0
Knowledge vs. Knowledge w/ EX	0	0
Knowledge vs. Quiz	0	0
Knowledge vs. T/F	0	0
Knowledge w/ EX vs. Quiz	0	0
Knowledge w/ EX vs. T/F	0	0
Quiz vs. T/F	8.6e-07	9.5e-07

Binomial

Note: These regressions are run on students who responded **at least** once

Some resources for binomal regression (for my reference):

- Logit / Probit
- Multilevel Modeling in R
- Intro to Generalized linear mixed models

Logit model

Run a bimodal regression based on `Question type` + `grade` + `race` + `gender` + `number of user's responses` + `Campaign number` (e.g. is it the first message sent, second sent, last message sent in the campaign). *In the future, can look at how category and/or keywords play into this.*

The next table (Table 6) shows the model in a more pretty table format. Table 7 shows the same model, but with an output more similar to SPSS.

Table 6: Fitting generalized (binomial/logit) linear model: Replied ~ Type + grade + race + gender + userResponses + campg.num

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-6.354	0.3701	-17.17	4.606e-66
TypeKnowledge	0.3154	0.3071	1.027	0.3044
TypeKnowledge w/ EX	3.931	0.2709	14.51	1.009e-47
TypeQuiz	4.912	0.2784	17.64	1.197e-69
TypeT/F	5.029	0.2737	18.38	2.05e-75
grade11	-0.09469	0.08896	-1.064	0.2871
grade12	-0.0538	0.08536	-0.6303	0.5285
grade7	0.07815	0.1302	0.6004	0.5482
grade8	0.03561	0.1804	0.1974	0.8435
grade9	-0.095	0.0932	-1.019	0.3081
raceAsian	0.1379	0.2794	0.4937	0.6215
raceBlack	0.2564	0.2511	1.021	0.3072
raceHispanic	0.1618	0.2426	0.6667	0.505
raceOther	0.2364	0.2966	0.797	0.4254
raceWhite	0.1511	0.2419	0.6248	0.5321
genderMale	-0.008795	0.06531	-0.1347	0.8929
genderOther	-0.1408	0.3921	-0.3591	0.7195
userResponses	0.1489	0.003566	41.76	0
campg.num	-0.03787	0.002095	-18.08	4.631e-73

Table 7: Table continues below

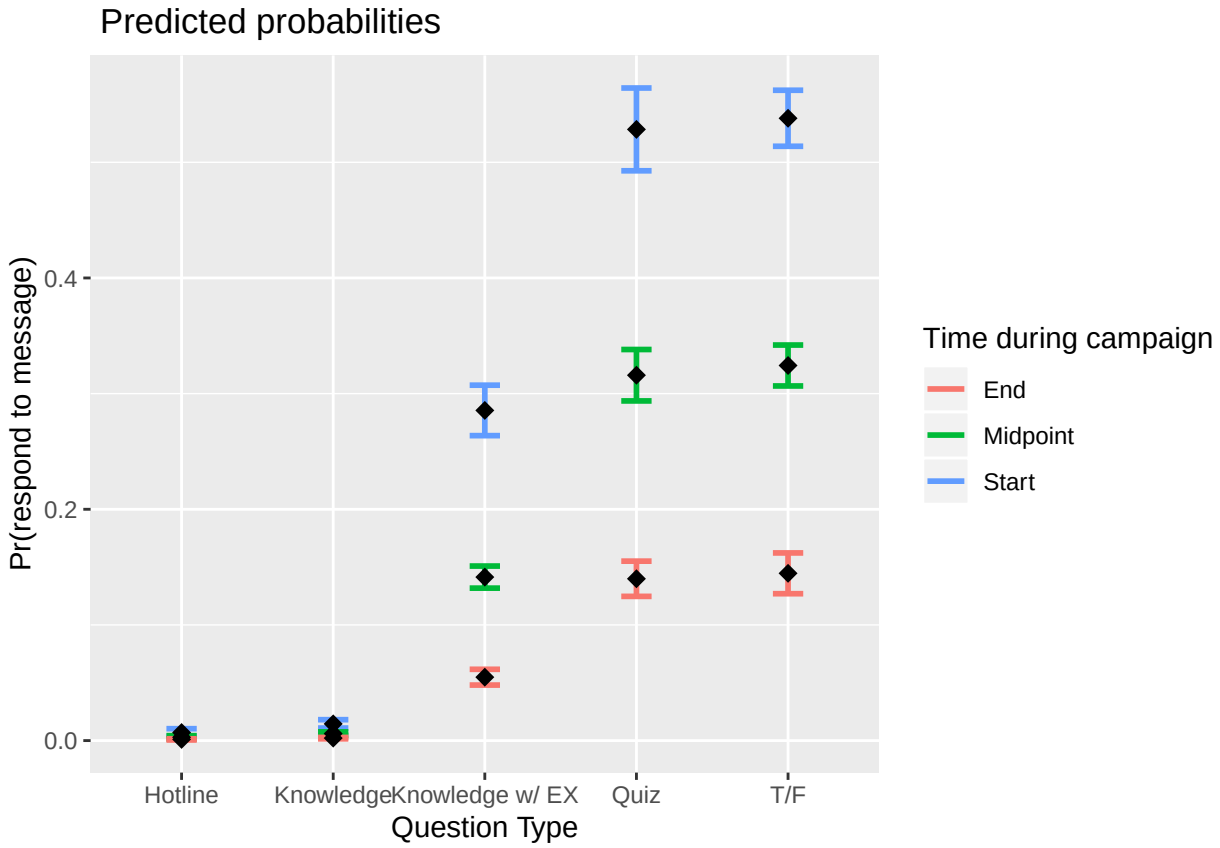
	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-6.354	0.3701	-17.17	0
TypeKnowledge	0.3154	0.3071	1.027	0.3044
TypeKnowledge w/ EX	3.931	0.2709	14.51	0
TypeQuiz	4.912	0.2784	17.64	0
TypeT/F	5.029	0.2737	18.38	0
grade11	-0.0947	0.089	-1.065	0.2871
grade12	-0.0538	0.0854	-0.6303	0.5285
grade7	0.0782	0.1302	0.6004	0.5482
grade8	0.0356	0.1804	0.1974	0.8435
grade9	-0.095	0.0932	-1.019	0.3081

	Estimate	Std. Error	z value	Pr(>|z|)
raceAsian	0.1379	0.2794	0.4937	0.6215
raceBlack	0.2564	0.2511	1.021	0.3072
raceHispanic	0.1618	0.2426	0.6667	0.505
raceOther	0.2364	0.2966	0.797	0.4254
raceWhite	0.1511	0.2419	0.6248	0.5321
genderMale	-0.0088	0.0653	-0.1347	0.8929
genderOther	-0.1408	0.3921	-0.3591	0.7195
userResponses	0.1489	0.0036	41.76	0
campg.num	-0.0379	0.0021	-18.08	0

	Exp(Estimate)	Exp(B) Lower95CI	Exp(B) Upper95CI
(Intercept)	0.0017	8e-04	0.0035
TypeKnowledge	1.371	0.7659	2.572
TypeKnowledge w/ EX	50.95	30.93	90.02
TypeQuiz	135.9	81.14	243.2
TypeT/F	152.7	92.17	271.1
grade11	0.9097	0.7641	1.083
grade12	0.9476	0.8017	1.12
grade7	1.081	0.8364	1.393
grade8	1.036	0.7232	1.468
grade9	0.9094	0.7574	1.091
raceAsian	1.148	0.6644	1.988
raceBlack	1.292	0.7918	2.121
raceHispanic	1.176	0.7322	1.897
raceOther	1.267	0.7072	2.264
raceWhite	1.163	0.7257	1.875
genderMale	0.9912	0.8718	1.126
genderOther	0.8687	0.3736	1.771
userResponses	1.161	1.153	1.169
campg.num	0.9628	0.9589	0.9668

Prediction

Based on modeling only the significant variables from above, which has a higher AIC (second model's AIC=`12,331`) than the model above (AIC=`8,090`). Note that the figure shows three points in time (beginning, midpoint, and end), but assumes `userResponses` is the same across the board



Multilevel logit model

The next output below models the **fixed effects** of variables of interest (e.g. question type) while accounting for **random effects** (`userID`). Note: the model doesn't converge if gender, race, or grade is included, presumably because those effects are accounted for in the random effects of the userID

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: Replied ~ Type + (1 | userID)
##    Data: df
##
##      AIC      BIC   logLik deviance df.resid
##  12952.6  12999.4  -6470.3  12940.6    18068
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.1588 -0.3957 -0.1975 -0.0403 24.7967
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  userID (Intercept) 2.119    1.456
## Number of obs: 18074, groups:  userID, 414
##
## Fixed effects:
##                     Estimate Std. Error z value Pr(>|z|)
```

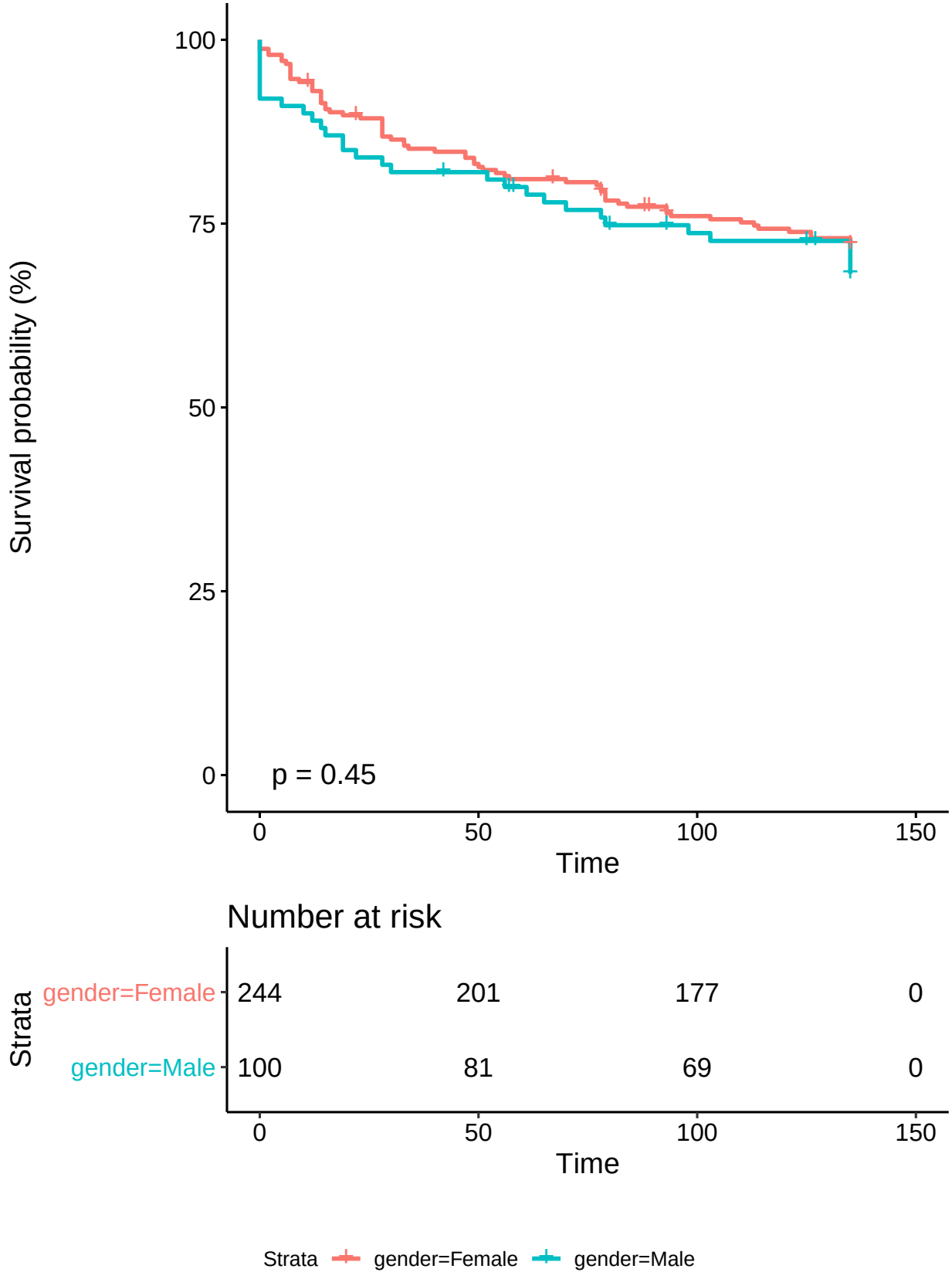
```
## (Intercept)          -5.3448     0.2489 -21.474   <2e-16 ***
## TypeKnowledge         0.5810     0.2626   2.212   0.0269 *
## TypeKnowledge w/ EX   3.4863     0.2392  14.572   <2e-16 ***
## TypeQuiz              4.2730     0.2426  17.613   <2e-16 ***
## TypeT/F               4.7069     0.2411  19.524   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) TypKnw TKw/EX TypeQz
## TypeKnowldg -0.842
## TypKnwlw/EX -0.942  0.876
## TypeQuiz    -0.934  0.864  0.967
## TypeT/F     -0.943  0.870  0.974  0.966
```

Survival analysis

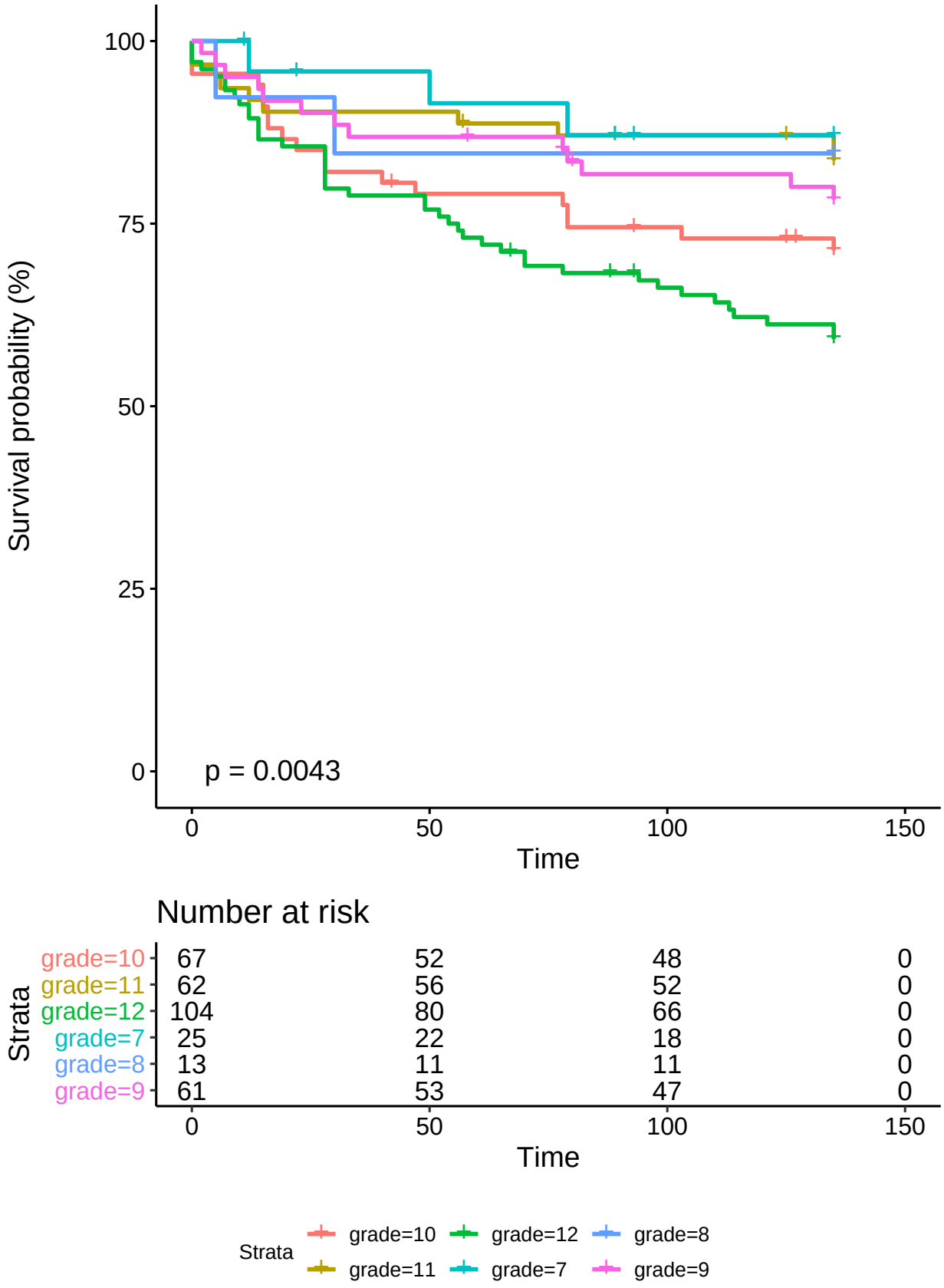
Some resources for survival analysis (for my reference):

- Comparing survival times between groups

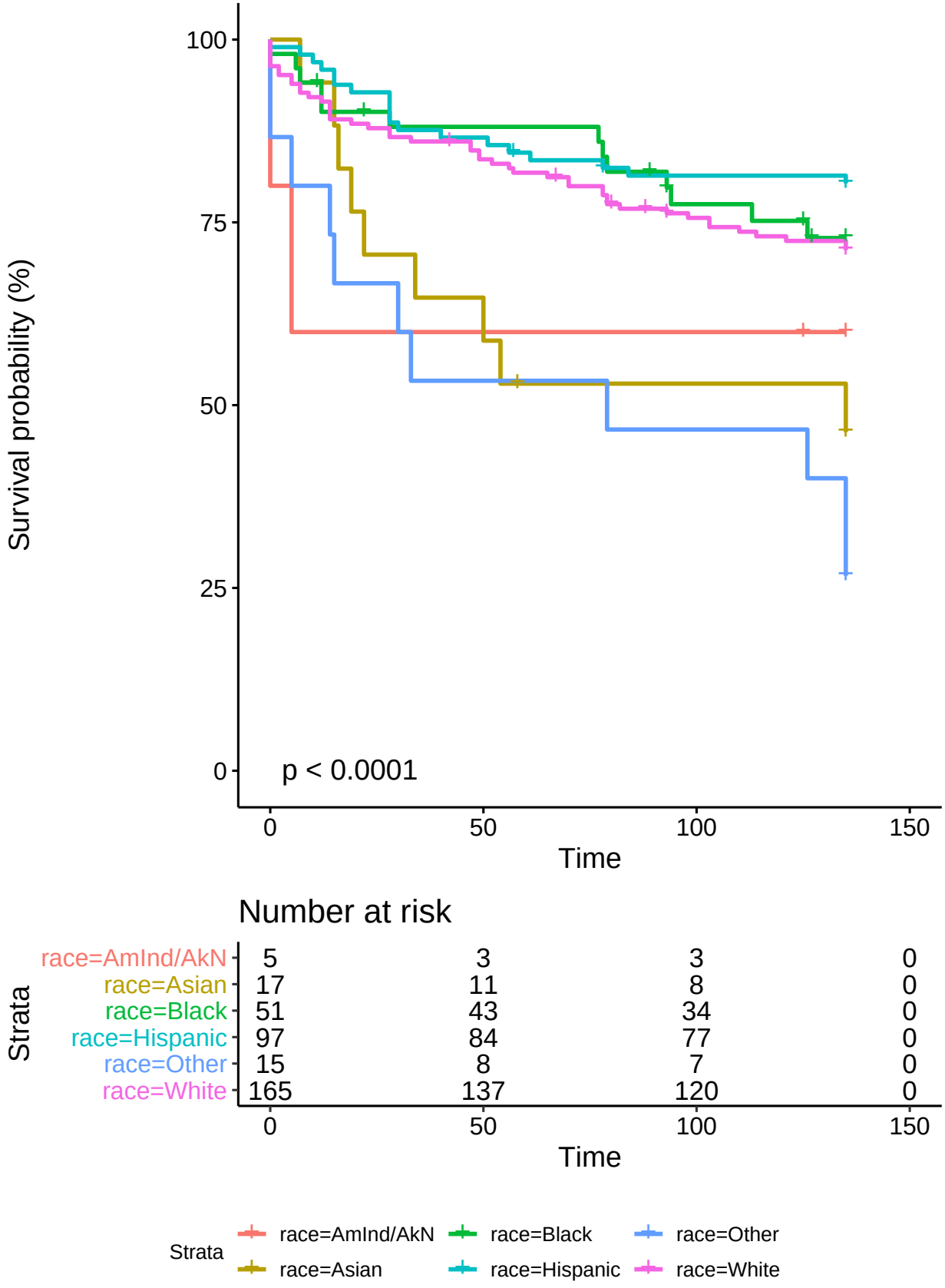
Gender


Survival probability (%)
100
75
50
25
0
p = 0.45
0
50
100
150
Time
Number at risk
Strata
gender=Female
gender=Male
244
201
177
0
100
81
69
0
0
50
100
150
Time
Strata
gender=Female
gender=Male

Grade


Survival probability (%)
100
75
50
25
0
p = 0.0043
0
50
100
150
Time
Number at risk
Strata
grade=10 67 52 48 0
grade=11 62 56 52 0
grade=12 104 80 66 0
grade=7 25 22 18 0
grade=8 13 11 11 0
grade=9 61 53 47 0
0
50
100
150
Time
Strata
grade=10
grade=12
grade=8
grade=11
grade=7
grade=9

Race


Survival probability (%)
100
75
50
25
0
p < 0.0001
0
50
100
150
Time
Number at risk
Strata
race=AmInd/AkN 5 3 3 0
race=Asian 17 11 8 0
race=Black 51 43 34 0
race=Hispanic 97 84 77 0
race=Other 15 8 7 0
race=White 165 137 120 0
0
50
100
150
Time
Strata
race=AmInd/AkN
race=Asian
race=Black
race=Hispanic
race=Other
race=White

Combo

Descriptive statistics

So there's quite a few `NA`'s (people who didn't have their gender, grade, or race recorded). A few people did respond to the gender & grade questions, but didn't fit into a larger category, so I dropped them from the analysis (total of 7 students)

Total number of students: 525

Gender

gender	n	sansNA	Percent
Female	238	72.1%	45.9%
NA	189	0.0%	36.4%
Male	92	27.9%	17.7%

Grade

grade	n	sansNA	Percent
NA	207	0.0%	39.5%
12	99	31.2%	18.9%
10	64	20.2%	12.2%
11	58	18.3%	11.1%
9	58	18.3%	11.1%
7	25	7.9%	4.8%
8	13	4.1%	2.5%

Race

Note that unlike gender & grade, I didn't drop the `Other` race because it's representing `Two or more races`

race	n	sansNA	Percent
NA	189	0.0%	36.0%
White	157	46.7%	29.9%
Hispanic	96	28.6%	18.3%
Black	50	14.9%	9.5%
Asian	17	5.1%	3.2%
Other	12	3.6%	2.3%
AmInd/AkN	4	1.2%	0.8%

Compare to Census data (2017 ACS 5-year estimates) from Galveston County:

Race	Percent
White (non-Hispanic)	45.9%
Hispanic or Latino	28.7%
Black or African American	20.8%

Race	Percent
Asian	3.2%
Two or more races	2.5%
American Indian and Alaska Native	0.5%