```
# The results indicate that there is not a significant correlation between recall accuracy and word count, readab
ility, polarity and subjectivity, with p-values of 0.8087, 0.6038, 0.1936 and 0.8217, respectively. So I will con
clude that there is not any correlation between accuracy and the predictor variables.
```

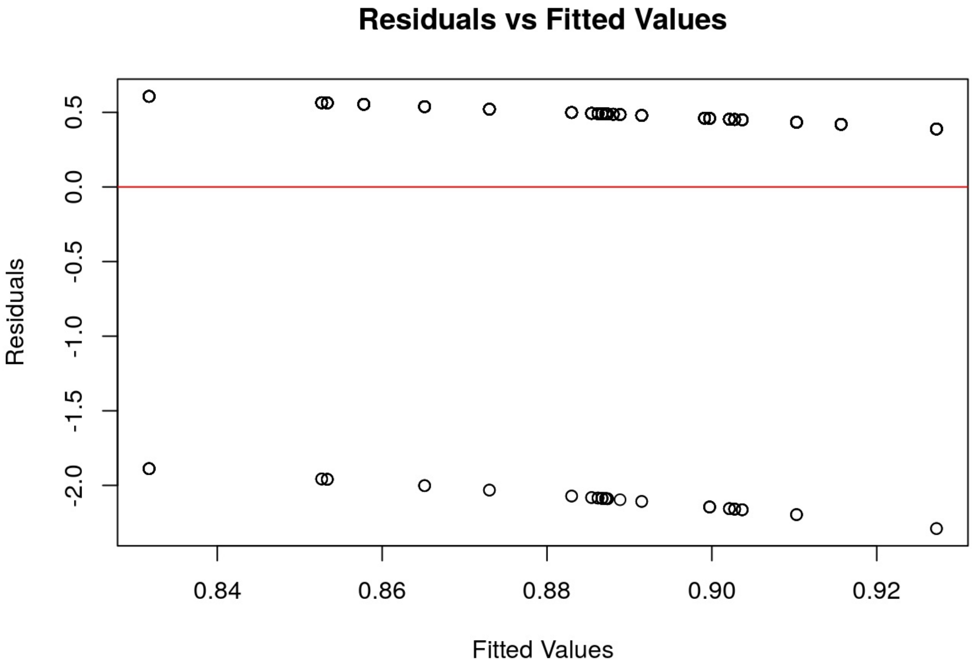
```
# I will now try to create a model with the accuracy column, which is binary, as the values can only be 1 for cor
rect or 0 for incorrect. I will also add predictors to the model. In cases with binary outcomes, specifically, lo
gistic regression is used. I will use a binomial Generalized Linear Mixed Model to handle the binary dependent va
riable and to account for participants as a source of variance.

model_logistic <- glmer(accuracy_numeric ~ number_of_words + readability + polarity + subjectivity + (1|ID), data
= df, family = binomial)

summary(model_logistic)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: accuracy_numeric ~ number_of_words + readability + polarity +
##     subjectivity + (1 | ID)
##    Data: df
##
##      AIC      BIC   logLik deviance df.resid
##    408.6    434.7   -198.3    396.6      559
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.5701  0.3265  0.3536  0.3640  0.4498
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  ID     (Intercept) 2.55e-14 1.597e-07
## Number of obs: 565, groups:  ID, 24
##
## Fixed effects:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)      2.07520    0.13483  15.392   <2e-16 ***
## number_of_words -0.13295    0.12488  -1.065    0.287
## readability      0.05991    0.17400   0.344    0.731
## polarity        -0.18355    0.13800  -1.330    0.183
## subjectivity     0.03914    0.17740   0.221    0.825
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) nmbr__ rdblty polrty
## nmbr_f_wrds -0.099
## readability  0.042 -0.146
## polarity    -0.139  0.152 -0.079
## subjectivty  0.035 -0.068  0.618 -0.213
## optimizer (Nelder_Mead) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')
```

```
residuals <- resid(model_logistic)
fitted_values <- fitted(model_logistic)
plot(fitted_values, residuals, main = "Residuals vs Fitted Values",
     xlab = "Fitted Values", ylab = "Residuals")
abline(h = 0, col = "red")
```



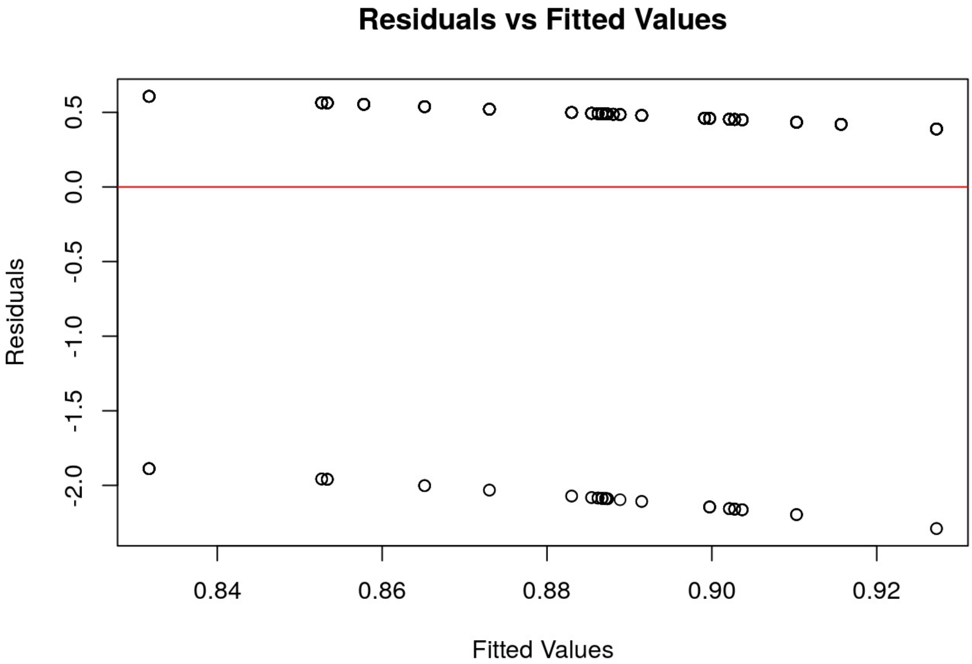

```
# The model is having trouble to estimate the random effects properly because there is very little variation. Thu
s, I will remove the random effect. The following model is a logistic regression model without random effects.

model_logistic_no_random <- glm(accuracy_numeric ~ number_of_words + readability + polarity + subjectivity, data
= df, family = binomial)

summary(model_logistic_no_random)
```

```
##
## Call:
## glm(formula = accuracy_numeric ~ number_of_words + readability +
##     polarity + subjectivity, family = binomial, data = df)
##
## Coefficients:
##                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)      2.07520    0.13483  15.392   <2e-16 ***
## number_of_words -0.13295    0.12488  -1.065    0.287
## readability      0.05991    0.17400   0.344    0.731
## polarity        -0.18355    0.13800  -1.330    0.183
## subjectivity     0.03914    0.17740   0.221    0.825
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 399.24  on 564  degrees of freedom
## Residual deviance: 396.65  on 560  degrees of freedom
## AIC: 406.65
##
## Number of Fisher Scoring iterations: 5
```

```
fitted_values <- fitted(model_logistic_no_random)
residuals <- residuals(model_logistic_no_random)
plot(fitted_values, residuals, main = "Residuals vs Fitted Values",
     xlab = "Fitted Values", ylab = "Residuals")
abline(h = 0, col = "red")
```




```
# In both cases, according to the results, the predictors of this model, which are word count, readability, polar
ity and subjectivity, do not significantly influence accuracy, with p-values of 0.287, 0.731, 0.183 and 0.825, re
spectively. They are all above the conventional threshold of 0.05.

# The assumption of homoscedasticity is not met in either case as the residuals vs fitted values plot shows becau
se there is a specific trend and the points are not scattered randomly. This is an important assumption and it is
violated so I will proceed with different research questions. My conclusion is that there is not a significant in
fluence of the independent variables on accuracy.
```

```
# Below I am going to look if people, on average, respond more quickly when giving a correct or an incorrect answ
er, and, if there is a difference, I want to know if it reaches significance. I will create a data frame where I
have the mean reaction time for their correct and incorrect responses, forming a pair for each participant. The d
ata between participants will of course be independent.

df_accuracy_by_participant <- df %>%
  group_by(ID, accuracy_numeric) %>%
  summarise(mean_rt = mean(inverse_power_rt, na.rm = TRUE))

df_accuracy_by_participant_final <- df_accuracy_by_participant %>%
  spread(accuracy_numeric, mean_rt) %>%
  rename(correct_rt = `1`, incorrect_rt = `0`)

# I will create an additional column where I calculate the difference between the mean reaction time for their co
rrect responses and that of their incorrect responses.

df_accuracy_by_participant_final$rt_difference <- df_accuracy_by_participant_final$correct_rt - df_accuracy_by_pa
rticipant_final$incorrect_rt

# I will remove points in my data more than 3 standard deviations away from the mean to ensure that I do not have
any outliers that distort the data.

mean_rt_diff <- mean(df_accuracy_by_participant_final$rt_difference, na.rm = TRUE)
sd_rt_diff <- sd(df_accuracy_by_participant_final$rt_difference, na.rm = TRUE)

threshold_upper <- mean_rt_diff + 3 * sd_rt_diff
threshold_lower <- mean_rt_diff - 3 * sd_rt_diff

df_accuracy_by_participant_final <- df_accuracy_by_participant_final %>%
  filter(rt_difference >= threshold_lower & rt_difference <= threshold_upper)

# As I have my data ready, I will conduct a one-sample t-test. I will see if the difference between the means is
significantly different from zero.

t_test_result <- t.test(df_accuracy_by_participant_final$rt_difference, mu = 0)
t_test_result
```

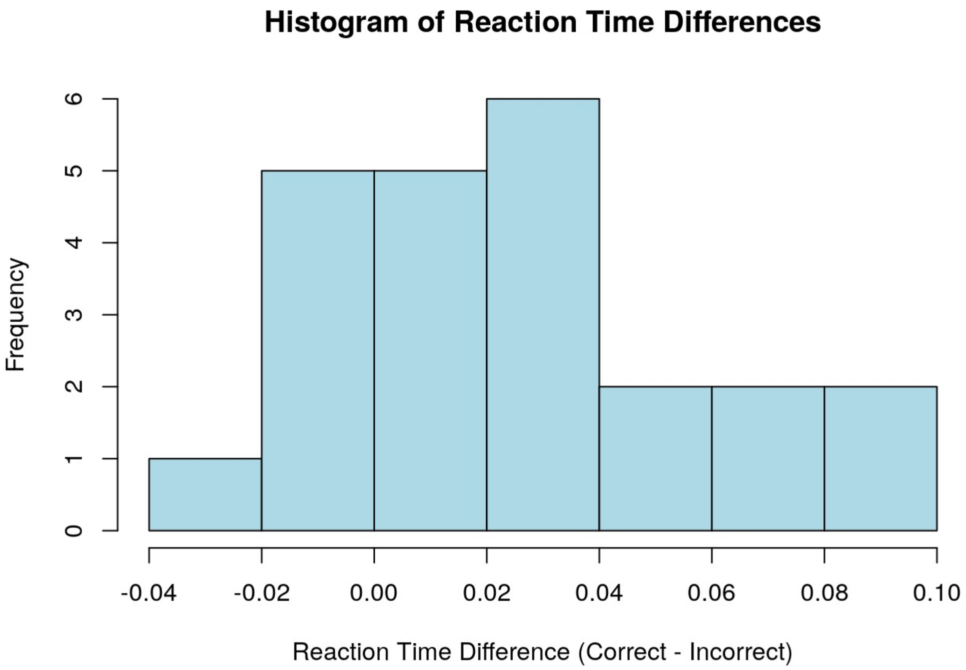
```
##
##  One Sample t-test
##
## data:  df_accuracy_by_participant_final$rt_difference
## t = 3.3618, df = 22, p-value = 0.002816
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
##  0.009076943 0.038308861
## sample estimates:
## mean of x
## 0.0236929
```

```
# One assumption is that the difference in reaction times has to be normally distributed. I will use both a numer
ic indicator, the p-value from a Shapiro-Wilk test, and visual means of checking for normality (histogram and QQ-
plot).

shapiro.test(df_accuracy_by_participant_final$rt_difference)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  df_accuracy_by_participant_final$rt_difference
## W = 0.95412, p-value = 0.3553
```

```
hist(df_accuracy_by_participant_final$rt_difference, main = "Histogram of Reaction Time Differences",
     xlab = "Reaction Time Difference (Correct - Incorrect)", col = "lightblue")
```




```
qqnorm(df_accuracy_by_participant_final$rt_difference)
qqline(df_accuracy_by_participant_final$rt_difference, col = "red")
```