Calvin University's Nursing VR Research

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Context

The goal of this experiment was to find if there was any correlation between the Nursing VR Experience - a experience where Calvin nursing students are able to practice in their nursing field through Virtual Reality - and whether this helped nursing students in confidence of health assessments.

We chose the following questions:

- How does the different time variables affect student's confidence for their health assessment?

- Does previous VR_Experience affect their confidence for the health assessment?

In which, we tried to explore the dataset given to us through surveys taken by students.

Challenges:

The first challenge that we stumbled across was that the data was all in paper format. This meant that all student responses had to be scanned and entered into a excel document manually for all the students that took this survey.

Our second challenge that we were faced with was that we now had all the data in our excel sheet, however, most of the entries were Qualitative data, which basically asked how confident were the students (Confident - Unconfident and the scale in between) before and after having the nursing simulation experience. Because there was no way of measuring qualitative data, we decided that we would manipulate the data and make our variables into quantitative data in which we would be able to combine questions and find the average score to overall find the average Knowledge and Confidence numbers of students during pre and post VR experience.

Explanations of Technical Documentation

Model Planning: Before we start building our model, we need to figure out what we're looking at. This involves:

- **Response Variable:** This is what we're trying to figure out or predict. Like, if we're studying how studying time affects student grades, then grades would be our response variable. In this case our response would be Confidence or Knowledge in health assessments.
- **Predictor Variable:** This is what we think might influence the response. So, in our example, the predictor variable would be studying time because we believe it affects grades. In this case our predictor variable would be Time_Point for both models.
- **Confounders:** These are variables that affect both predictor and response. An example includes a study comparing teaching methods and math test scores, a confounder could be students' natural aptitude for math. If one group naturally excels in math more than the other, it could influence both their test scores and their preference for a teaching method, potentially skewing the results.
- There are other variables as well, however, for our dataset, we only included confounders so that is all that we will be specifying for now.

Model Fitting: This is where we try to find the best way to represent our data using our chosen variables. In our model, a linear regression is used when we want to understand and predict the relationship between two or more continuous variables. It's particularly useful for finding patterns or trends in data and making predictions based on those patterns.

Model Assessment: Once we've built our model, we need to check if it's any good. We do this by testing how well it fits our data and if it can actually make useful predictions. For different regressions, we test different things, however, since we are using a linear regression model, we need to test for:
Linearity

Independence of Residuals

Normality

Error Variance

Model Selection: Next, we explore model selection. Model selection involves choosing the best model among a set of candidate models. For this experiment, we used an Anova table and Hypothesis testing. The anova table showed us p-values of the variables we used in our model, and it is used for evidence as to whether a variable affects our main response or not. Next, we used hypothesis testing in order to compare pairwise the different time points which further gives us evidence as to whether our main predictor, time point, affected our response.

Prediction Plot: Finally, we had the prediction plot. A prediction plot visualizes the relationship between predictor variables and the response variable based on a fitted model.It provides a graphical representation of the model's predictions, allowing for easier interpretation and understanding of the model's behavior across different values of predictors. Prediction plots can help to identify trends, patterns, and outliers, and they are useful for validating the model's predictions against the actual data. For our prediction plot, it shows that Time Point shows importance as Pre test and Post test findings differed by a substantial amount.

Understanding the context of our dataset, the following below is the technical documentation that we have done for the data.

Data

Our data set was particularly tricky as we had to manually enter data from a survey format from nursing students given to by Professor Kunnen, into a spreadsheet, in which we converted to a CSV and read it in below.

- How does the different time variables affect student's confidence for their health assessment?
- Does previous VR_Experience affect their confidence for the health assessment?

Lists of Measures in our Dataset

1. Participant ID: Unique identifier for each participant
2. Test entry point: When the students took the test, pre, post, and 2 months after using VR goggles (Categorical)
3. Questionnaire Responses: Responses to a series of questions, relating to experience of gaming, and using VR goggles, where choices were A, U, SA, and D, showing the students confidence levels.
4. Age: Age of participant (Categorical)
5. Gender: Male or female (Binary data one trial)
6. Ethnicity/Race: Ethnicity of participant (Binary data multiple trials)
7. Year of college: What the participants level of education was (Binary data multiple trials)

Data manipulation and mutations

```
prepost_num <- prepost |>
  mutate(across(Health_Assessment:Assesment_Data_Knowledge_Confidence,
              ~case_when(.x == 'SA' ~ 4,
                         .x == 'A' ~ 3,
                         .x == 'U' ~ 2,
                         .x == 'D' ~ 1,
                         .x == 'SD' ~ 0),
              # new numeric columns will have names like the original columns,
              # but with "_num" appended
              .names = "{.col}_num"),
```

```r
         knowledge_num = (Health_Assessment_num
                          + Nursing_Process_num
                          + Nursing_Interventions_num
                          + Assesment_Data_Knowledge_num) / 4,
         confidence_num = (Confidence_of_Health_Assesment_num
                           + Acute_Care_Nursing_Interventions_Confidence_num
                           + Severe_Care_Nursing_Intervention_Confidence_num
                           + Assesment_Data_Knowledge_Confidence_num) / 4
         )

prepost_num <- prepost_num |>

  mutate(Simulation_Experience =
           case_when(Actual_Simulation_Expiriences %in%
                       c('Reality_Gaming_Exp',
                         'Gaming_and_Goggles',
                         'Reality_Goggles',
                         'Reality_Gaming')
                     ~ 'Previous Experience',
                     Actual_Simulation_Expiriences ==
                       'First' ~ 'No Experience'),

         Year_Of_College = factor(Year_Of_College),

         Gender = factor(Gender)
         )

mosaic::tally(~knowledge_num, data = prepost_num)
```

```
Registered S3 method overwritten by 'mosaic':
  method                           from
  fortify.SpatialPolygonsDataFrame ggplot2
```

```
knowledge_num
 0.5  1.5 1.75    2 2.25  2.5 2.75    3 3.25  3.5 3.75    4 <NA>
   1    1    2    5   13   20   26   36   21   14    3    4    5
```

```r
mosaic::tally(~confidence_num, data = prepost_num)
```

```
confidence_num
   1 1.25  1.5 1.75    2 2.25  2.5 2.75    3 3.25  3.5 3.75    4
   3    2    4    2    8   18   23   29   41    7    7    2    5
```

```r
glimpse(prepost_num)
```

```
Rows: 151
Columns: 27
$ Student_ID                                       <dbl> 1, 1, 2, 2, 3, 3, 4, 4~
$ Time_Point                                       <chr> "Pre-test", "Post-test~
$ Health_Assessment                                <chr> "SA", "SA", "U", "U", ~
$ Nursing_Process                                  <chr> "SA", "SA", "A", "U", ~
$ Nursing_Interventions                            <chr> "A", "A", "A", "A", "A~
$ Assesment_Data_Knowledge                         <chr> "U", "A", "U", "A", "A~
$ Confidence_of_Health_Assesment                   <chr> "U", "A", "U", "U", "A~
$ Acute_Care_Nursing_Interventions_Confidence      <chr> "A", "A", "A", "U", "U~
$ Severe_Care_Nursing_Intervention_Confidence      <chr> "U", "A", "A", "U", "U~
$ Assesment_Data_Knowledge_Confidence              <chr> "A", "A", "A", "U", "U~
$ Year_Of_College                                  <fct> J3, J3, J3, J3, J3, J3~
$ Previous_Simulation_Experiences                  <chr> "Not_Similiar", "Not_S~
$ Age                                              <dbl> 20, 20, 20, 20, 20, 20~
$ Gender                                           <fct> Male, Male, Female, Fe~
$ Race_Ethnicity                                   <chr> "Asian_American", "Asi~
$ Actual_Simulation_Expiriences                    <chr> "Reality_Gaming", "Rea~
$ Health_Assessment_num                            <dbl> 4, 4, 2, 2, 2, 3, 2, 3~
$ Nursing_Process_num                              <dbl> 4, 4, 3, 2, 2, 2, 3, 3~
$ Nursing_Interventions_num                        <dbl> 3, 3, 3, 3, 3, 3, 3, 3~
$ Assesment_Data_Knowledge_num                     <dbl> 2, 3, 2, 3, 3, 3, 3, 3~
$ Confidence_of_Health_Assesment_num               <dbl> 2, 3, 2, 2, 3, 3, 2, 2~
$ Acute_Care_Nursing_Interventions_Confidence_num <dbl> 3, 3, 3, 2, 2, 2, 3, 3~
$ Severe_Care_Nursing_Intervention_Confidence_num <dbl> 2, 3, 3, 2, 2, 2, 3, 3~
$ Assesment_Data_Knowledge_Confidence_num          <dbl> 3, 3, 3, 2, 2, 2, 3, 3~
$ knowledge_num                                    <dbl> 3.25, 3.50, 2.50, 2.50~
$ confidence_num                                   <dbl> 2.50, 3.00, 2.75, 2.00~
$ Simulation_Experience                            <chr> "Previous Experience",~
```

Description We included 2 questions and for each question we found the average of all quantitative variables we used in the model and put this into one variable, either knowledge_num or confidence_num. By doing so, it gave us a measurement for the self assessed knowledge and confidence.

Question 1

We are curious if using the VR simulation increases the nurses' knowledge about health assessments, so we created a new data set to investigate. We will be focusing on Time_Point as our key_factor because it the variable that measures if they had done the VR simulation. This exploration will help us understand how the VR simulation influences the nurses' knowledge about health assessments.

Thus, our first research question that we are trying to explore is: How does the different time variables affect student's knowledge about health assessments?

Model Plan

Response Variable: knowledge_num

Predictor Variable: Time_Point

Confounders: No confounders

Precision Covariates: Year_Of_College, Gender, Simulation_Experience

Mediation Chain: No mediation chain

Collider: No colliders

Rationale Looking at the n/15 rule, we are only able to use 10 parameters as we have 151 rows of data. Because of this, we decided to only include data that we thought was relevant to analyze the relationship between our main response and predictor. We only are only allowed 10 parameters, we were limited on the amount of variables to choose as we did not want to overfit the model.

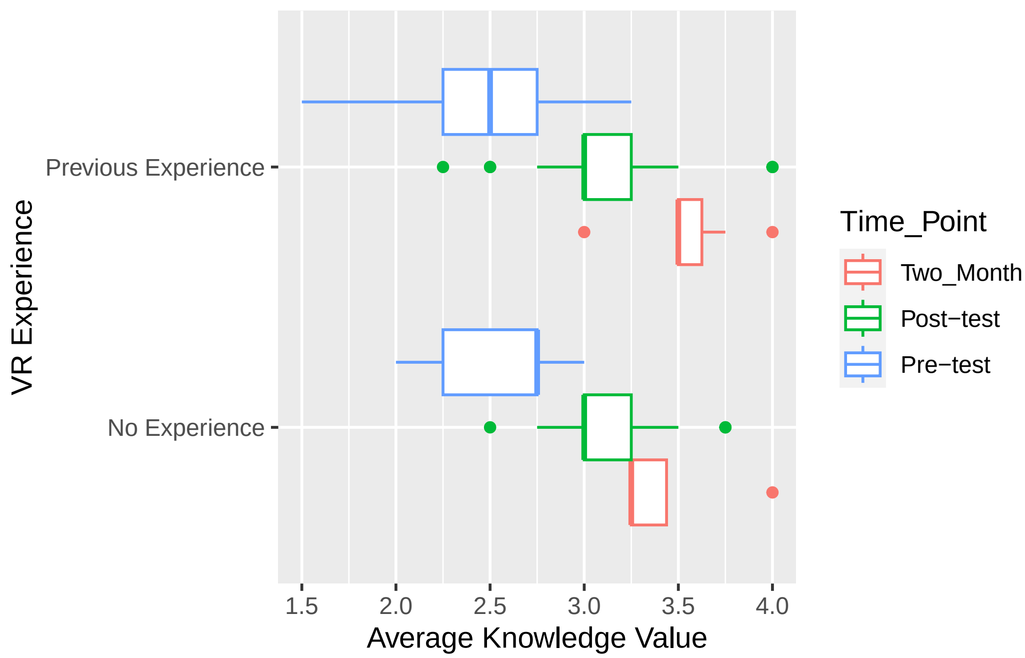
We chose to use a Linear Regression as we are using continuous quantitative data, also because of the advice Professor DeRuiter gave us, we decided that linear regression was the best decision for our model.

Knowledge Graphics

Understanding the data that we will be trying to explore, we will first explore our data by creating a box plot.

```
knowledge <- prepost_num |>
  select(knowledge_num, Simulation_Experience,
         Year_Of_College, Gender, Time_Point) |>
  drop_na() |>
  mutate(Time_Point = fct_relevel(Time_Point,
```

```
                                        "Two_Month",
                                        "Post-test",
                                        "Pre-test"))

gf_boxplot(knowledge_num ~ Simulation_Experience,
           color=~Time_Point, data = knowledge) |>
  gf_refine(coord_flip()) |>
  gf_labs(x="VR Experience",
          y="Average Knowledge Value")
```



Analysis of Graph We chose to use boxplots because they work well with both qual-itative and quantitative data. This type of plot is great because it doesn't stack the data,showing each data point clearly for better accuracy. The choice to use a boxplot was also determined because it best suited our needs to show a side by side relation and comparison on how previous VR simulation experience affects knowledge number ratings and how that changes with doing the nursing VR simulation.

Looking closer at the boxplot, we can see a trend. It appears that nurses that have done the nursing VR simulation (Post-Test) have a higher knowledge rating than they did before the VR simulation. We can also see that there is some variation between if the person has had previous VR experience those who have not. We will need to look further to see if that is just noise.

Model Fitting

Next, we move on to model fitting to further explore the data. Our main predictor will be Time_Point as we want to compare the different time intervals since the nurses took the assessments, however, we will be including an interaction with whether or not these individuals had VR experiences, as we wanted to explore whether this played a factor in predicting the response.

Knowledge regression

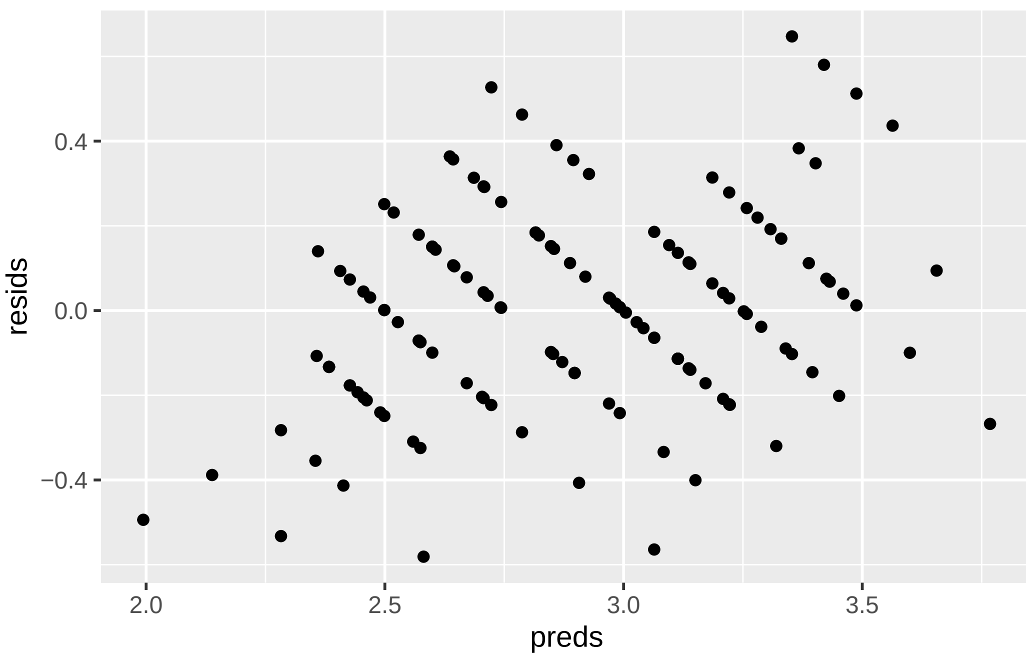
```r
knowledge_model <- glmmTMB(
  knowledge_num ~ Time_Point * Simulation_Experience +
    Year_Of_College + Gender + (1 | Student_ID),
    data = prepost_num,
)

options(scipen = 999) # Makes the results in non scientific notation

summary(knowledge_model)
```

```
 Family: gaussian  ( identity )
Formula:
knowledge_num ~ Time_Point * Simulation_Experience + Year_Of_College +
    Gender + (1 | Student_ID)
Data: prepost_num

     AIC      BIC   logLik deviance df.resid
   114.5    144.2    -47.3     94.5      133

Random effects:

Conditional model:
 Groups     Name        Variance Std.Dev.
 Student_ID (Intercept) 0.05095  0.2257
 Residual               0.07472  0.2733
Number of obs: 143, groups:  Student_ID, 67

Dispersion estimate for gaussian family (sigma^2): 0.0747

Conditional model:
```

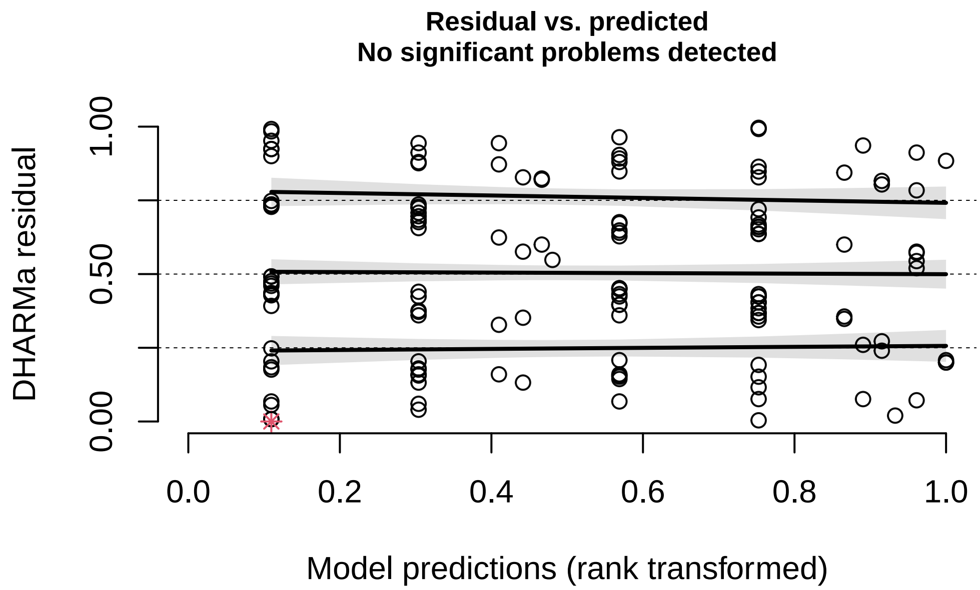
```
                                                             Estimate
(Intercept)                                                   3.08871
Time_PointPre-test                                           -0.51439
Time_PointTwo_Month                                           0.46794
Simulation_ExperiencePrevious Experience                      0.01858
Year_Of_CollegeJ4                                             0.08685
GenderMale                                                    0.08344
Time_PointPre-test:Simulation_ExperiencePrevious Experience  -0.05099
Time_PointTwo_Month:Simulation_ExperiencePrevious Experience -0.12011
                                                             Std. Error z value
(Intercept)                                                     0.06597   46.82
Time_PointPre-test                                              0.06950   -7.40
Time_PointTwo_Month                                             0.16222    2.88
Simulation_ExperiencePrevious Experience                        0.08857    0.21
Year_Of_CollegeJ4                                               0.15524    0.56
GenderMale                                                      0.10380    0.80
Time_PointPre-test:Simulation_ExperiencePrevious Experience     0.09627   -0.53
Time_PointTwo_Month:Simulation_ExperiencePrevious Experience    0.20607   -0.58
                                                                         Pr(>|z|)
(Intercept)                                                  < 0.0000000000000002
Time_PointPre-test                                              0.000000000000134
Time_PointTwo_Month                                                       0.00392
Simulation_ExperiencePrevious Experience                                  0.83381
Year_Of_CollegeJ4                                                         0.57584
GenderMale                                                                0.42147
Time_PointPre-test:Simulation_ExperiencePrevious Experience               0.59631
Time_PointTwo_Month:Simulation_ExperiencePrevious Experience              0.55998

(Intercept)                                                  ***
Time_PointPre-test                                           ***
Time_PointTwo_Month                                          **
Simulation_ExperiencePrevious Experience
Year_Of_CollegeJ4
GenderMale
Time_PointPre-test:Simulation_ExperiencePrevious Experience
Time_PointTwo_Month:Simulation_ExperiencePrevious Experience
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Knowledge Model Assessments

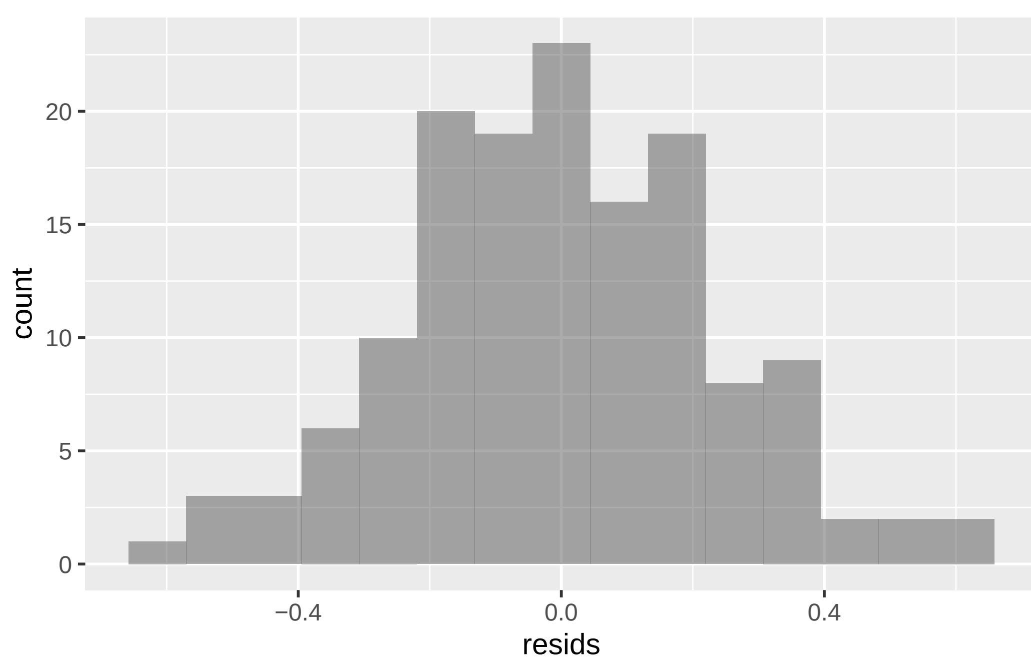
```
# Create model dataframe with non-NA values
model <- prepost_num |>
  select(Student_ID, knowledge_num, Year_Of_College, Gender,
         Time_Point, Simulation_Experience) |>
  drop_na()

# Make predictions using the fitted model
preds <- predict(knowledge_model, newdata = model)

# Calculate residuals
resids <- resid(knowledge_model)

# Residuals vs. fitted values plot
gf_point(resids ~ preds, data = model)
```



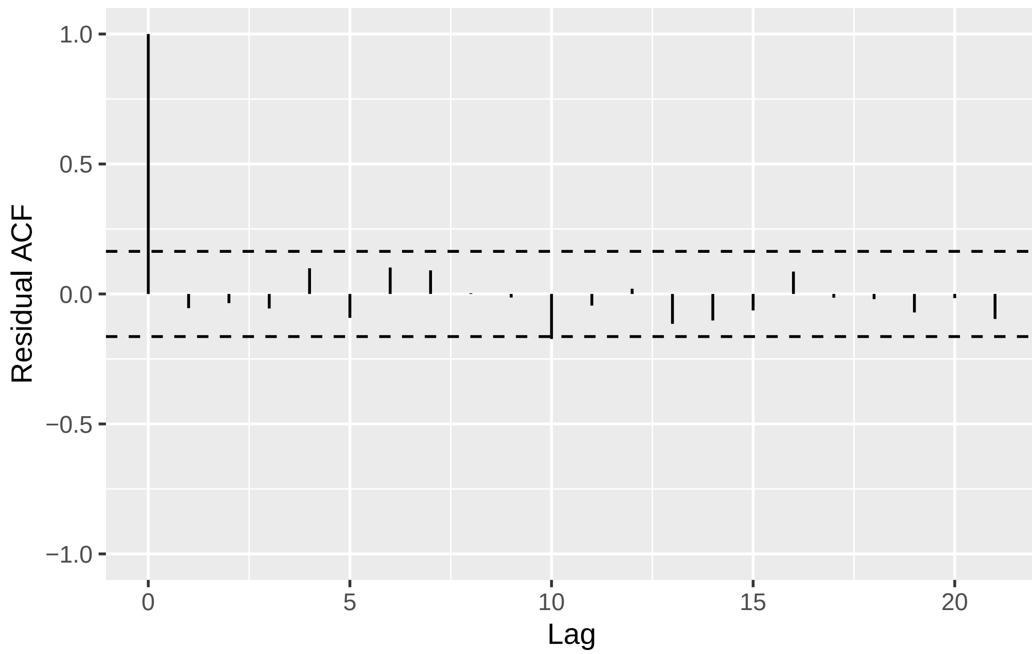

```
# could also use scaled residuals since there is a RE now
plotResiduals(simulateResiduals(knowledge_model))
```




```r
# Histogram of residuals
gf_histogram(~resids, data = model, bins = 15)
```



```
# ACF plot
s245::gf_acf(~ resids) |>  # Pass theula here
  gf_lims(y = c(-1, 1))
```



Analysis of Knowledge

Looking at our assessments, it seems that all of our assessments are able to pass. For Linearity, the scaled residuals plot shows no trends, which allows us to conclude that linearity passes. For the normality test we will look at the histogram. It seems to pass, it is a normal distribution and it is symmetric. Our scatterplot point cloud also seemsto fit well in a rectangle, which means that our error variance assessment passes. Then looking at our ACF plot, shows that the Independence assessment passes because all of the lags are within the bounds. Since all our tests pass, we are able to move on to model selection and draw conclusions for this model.

Model Selection

Next, we are able to go on to Model Selection to further explore whether the main predic-tor plays a role in affecting nurses' knowledge about health assessments.

```
# no_Time_Point <- lm(knowledge_num ~ Year_Of_College + Gender + Simulation_Experience, da
```

```r
car::Anova(knowledge_model)
```

```
Warning in printHypothesis(L, rhs, names(b)): one or more coefficients in the hypothesis incl
     arithmetic operators in their names;
  the printed representation of the hypothesis will be omitted

Warning in printHypothesis(L, rhs, names(b)): one or more coefficients in the hypothesis incl
     arithmetic operators in their names;
  the printed representation of the hypothesis will be omitted

Warning in printHypothesis(L, rhs, names(b)): one or more coefficients in the hypothesis incl
     arithmetic operators in their names;
  the printed representation of the hypothesis will be omitted
```

```
Analysis of Deviance Table (Type II Wald chisquare tests)

Response: knowledge_num
                                  Chisq Df          Pr(>Chisq)    
Time_Point                     177.2778  2 <0.0000000000000002 ***
Simulation_Experience            0.0347  1              0.8522    
Year_Of_College                  0.3130  1              0.5758    
Gender                           0.6462  1              0.4215    
Time_Point:Simulation_Experience   0.5030  2              0.7776    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
pairwise_time_point <- emmeans(knowledge_model,
                        specs = ~Time_Point | Simulation_Experience)

pairs(pairwise_time_point)
```

```
Simulation_Experience = No Experience:
 contrast                 estimate     SE  df t.ratio p.value
 (Post-test) - (Pre-test)    0.514 0.0695 133   7.402  <.0001
 (Post-test) - Two_Month    -0.468 0.1622 133  -2.885  0.0126
 (Pre-test) - Two_Month     -0.982 0.1622 133  -6.058  <.0001

Simulation_Experience = Previous Experience:
 contrast                 estimate     SE  df t.ratio p.value
```

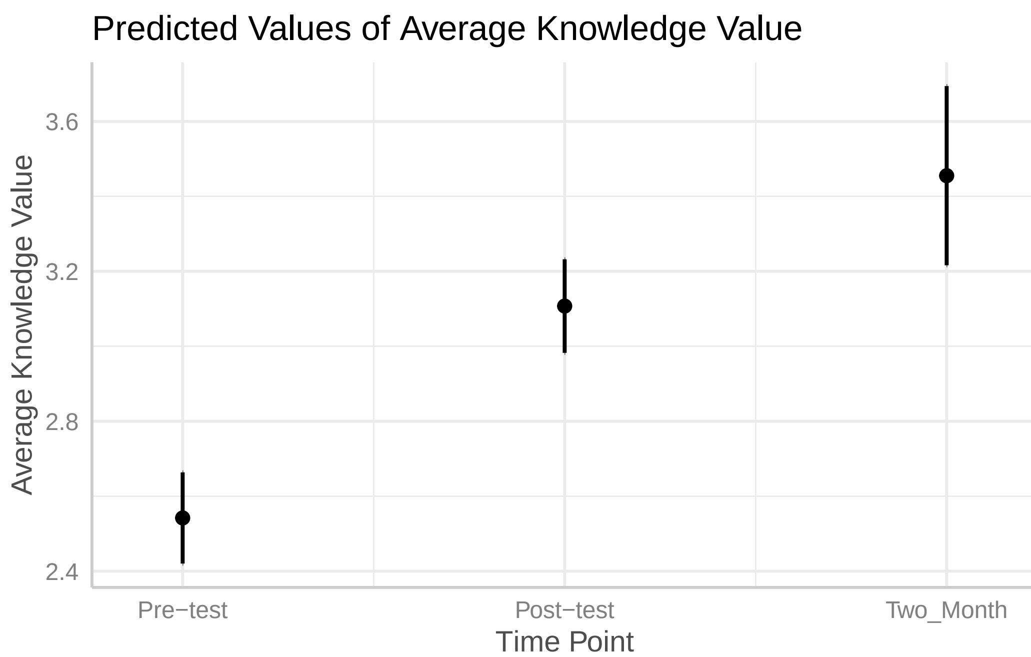
```
 (Post-test) - (Pre-test)    0.565 0.0663 133   8.526  <.0001
 (Post-test) - Two_Month    -0.348 0.1250 133  -2.783  0.0169
 (Pre-test) - Two_Month     -0.913 0.1247 133  -7.325  <.0001

Results are averaged over the levels of: Year_Of_College, Gender
P value adjustment: tukey method for comparing a family of 3 estimates
```

Here the overall ANOVA results show indicate that there is no evidence of an interaction between time point and simulation experience, nor of main effects of simulation experience, year of college, or gender. There is, however, very strong evidence of a consistent overall effect of time point, with higher scores after the simulation exercise and even higher scores two months later.

We also did post-hoc pairwise comparisons to determine which time-points differ (using Tukey's method to adjust p-values for multiple comparisons). To do this, we used the R package `emmeans` and its functions `emmeans()` and `pairs()`. The p-values for the test of the null hypothesis that confidence scores were the same pre- and post- exercise were less than 0.0001 for comparing pre- to both immediate post and two months post. In both cases the results indicate higher knowledge scores after the exercise - by about 0.57 points right after the exercise and about 0.91 points two months after. There was also moderate evidence of a statistically detectable difference between the post- and two-month scores ($p = 0.0169$ for the group with simulation experience, and 0.0126 for the group without prior experience), with higher scores at 2 months by about 0.47 or 0.35 respectively.

Prediction Plot

```r
ggpredict(knowledge_model,
          terms = c('Time_Point'),
          type = 'fixed') |>
  plot() |>
  gf_labs(title='Predicted Values of Average Knowledge Value',
          x='Time Point',
          y='Average Knowledge Value')
```



Analysis of Prediction Plot

In this analysis, we are looking at a model that looks at how after doing the nursing VR simulation influences their knowledge about health assessments. This fits our goal of seeing the positive correlation of doing the nursing VR simulation with the increase of knowledge.

Looking at the prediction plot, we can see that immediately after trying the nursing VR simulation that there is an increase in knowledge of the health assessments. This signifies that time point definitely matters in our model analysis.

Conclusions

Key Findings

Question 1 Answer: Overall, our analysis shows that trying the nursing VR simulation has a positive correlation of gaining more knowledge of health assessments.

Question 2

We were curious about whether nurses' past VR experiences affected their confidence in health assessments, so we created a new dataset to investigate. Even though our initial data analysis didn't go as planned, we're still focusing on Time_Point as a key factor. We're particularly interested in how Time_Point interacts with Simulation_Experiences. This exploration will help us understand how previous VR exposure influences nurses' confidence in health assessments.

Thus, our second research question that we are trying to explore is: Does previous VR_Experience affect their confidence for the health assessment?

Model Plan

Response Variable: confidence_num

Predictor Variable: Time_Point

Interaction: Simulation_Experience

Confounders: No confounders

Precision Covariates: Year_Of_College, Gender

Mediation Chain: No mediation chain

Collider: No colliders

Rationale Like the above, because of the n/15 rule, we are only able to use 10 parameters as we have 151 rows of data. Because of this, we decided to only include data that we thought was relevant to analyze the relationship between our main response and predictor. Because we only were allowed 10 parameters, we were limited on the amount of variables to choose as we did not want to overfit the model.

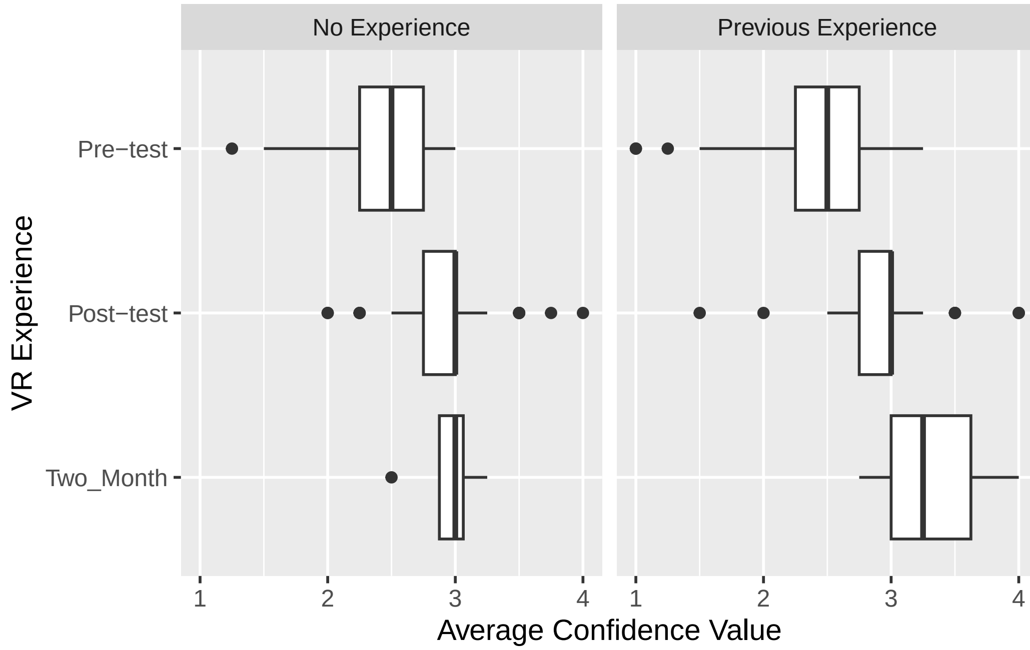
Again, we chose to use a Linear Regression as we are using continuous quantitative data.

Confidence Graphics

Understanding the data that we will be trying to explore, we will first explore our data by creating a box plot

```
confidence <- prepost_num |> drop_na() |>
  select(confidence_num, Year_Of_College, Gender,
         Time_Point, Simulation_Experience) |>
  drop_na() |>
  mutate(Time_Point = fct_relevel(Time_Point,
                                  "Two_Month",
                                  "Post-test",
                                  "Pre-test"))

gf_boxplot(confidence_num ~ Time_Point | Simulation_Experience, data = confidence) |>
```

```
gf_refine(coord_flip()) |>
gf_labs(x="VR Experience",
        y="Average Confidence Value")
```



Analysis of the Graphic We chose to use boxplots because they work well with both qualitative and quantitative data. This type of plot is great because it doesn't stack the data, showing each data point clearly for better accuracy.

Looking at the boxplot, we noticed a trend. It seems that after two months, nurses tend to be more confident in their health assessments. Also, when we considered the interaction with previous simulation experiences, we saw that after two months, nurses who had those experiences tended to have a higher median confidence level. Nevertheless, the response did not change for Pre and Post tests in terms of having previous or no experience with simulation. Thus, the interaction, Simulation_Experience seems like it does not affect the response, however, we still need to further explore the data to come into this conclusion.

Model Fitting

Next, we move on to model fitting to further explore the data.

```r
confidence_model <- glmmTMB(
  confidence_num ~ Time_Point * Simulation_Experience +
    Year_Of_College + Gender + (1 | Student_ID),
    data = prepost_num,
)

  options(scipen = 999) # Makes the results in non scientific notation

summary(confidence_model)
```

```
 Family: gaussian  ( identity )
Formula:
confidence_num ~ Time_Point * Simulation_Experience + Year_Of_College +
    Gender + (1 | Student_ID)
Data: prepost_num

     AIC      BIC   logLik deviance df.resid
   201.5    231.5    -90.7    181.5      138

Random effects:

Conditional model:
 Groups     Name        Variance Std.Dev.
 Student_ID (Intercept) 0.09047  0.3008
 Residual               0.13140  0.3625
Number of obs: 148, groups:  Student_ID, 68

Dispersion estimate for gaussian family (sigma^2): 0.131

Conditional model:
                                                            Estimate
(Intercept)                                                  2.86784
Time_PointPre-test                                          -0.47516
Time_PointTwo_Month                                          0.27184
Simulation_ExperiencePrevious Experience                     0.08025
Year_Of_CollegeJ4                                            0.15729
GenderMale                                                   0.07909
Time_PointPre-test:Simulation_ExperiencePrevious Experience  -0.11909
Time_PointTwo_Month:Simulation_ExperiencePrevious Experience -0.03808
                                                            Std. Error z value
(Intercept)                                                    0.08508   33.71
```

```
Time_PointPre-test                                              0.08972   -5.30
Time_PointTwo_Month                                             0.21581    1.26
Simulation_ExperiencePrevious Experience                        0.11565    0.69
Year_Of_CollegeJ4                                               0.20614    0.76
GenderMale                                                      0.13618    0.58
Time_PointPre-test:Simulation_ExperiencePrevious Experience     0.12523   -0.95
Time_PointTwo_Month:Simulation_ExperiencePrevious Experience    0.27223   -0.14
                                                                         Pr(>|z|)
(Intercept)                                                  < 0.0000000000000002
Time_PointPre-test                                                    0.000000118
Time_PointTwo_Month                                                         0.208
Simulation_ExperiencePrevious Experience                                    0.488
Year_Of_CollegeJ4                                                           0.445
GenderMale                                                                  0.561
Time_PointPre-test:Simulation_ExperiencePrevious Experience                 0.342
Time_PointTwo_Month:Simulation_ExperiencePrevious Experience                0.889

(Intercept)                                                  ***
Time_PointPre-test                                           ***
Time_PointTwo_Month
Simulation_ExperiencePrevious Experience
Year_Of_CollegeJ4
GenderMale
Time_PointPre-test:Simulation_ExperiencePrevious Experience
Time_PointTwo_Month:Simulation_ExperiencePrevious Experience
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

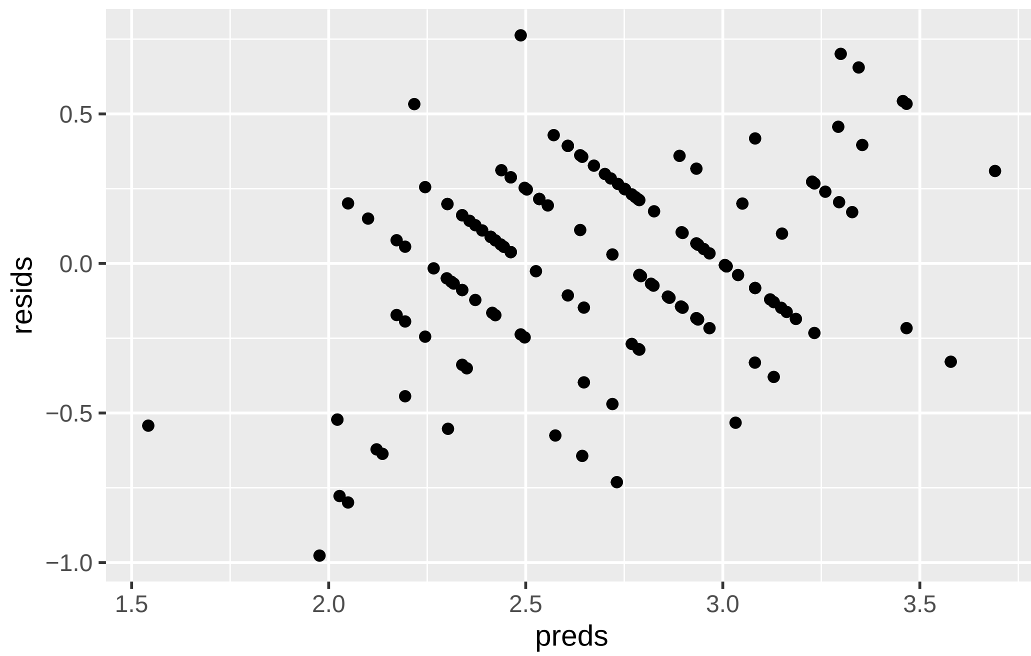
Model Assessments

We then will use the model regression to explore model assessments. Since we are working with a Linear Regression model, we would need to check the following assessments:

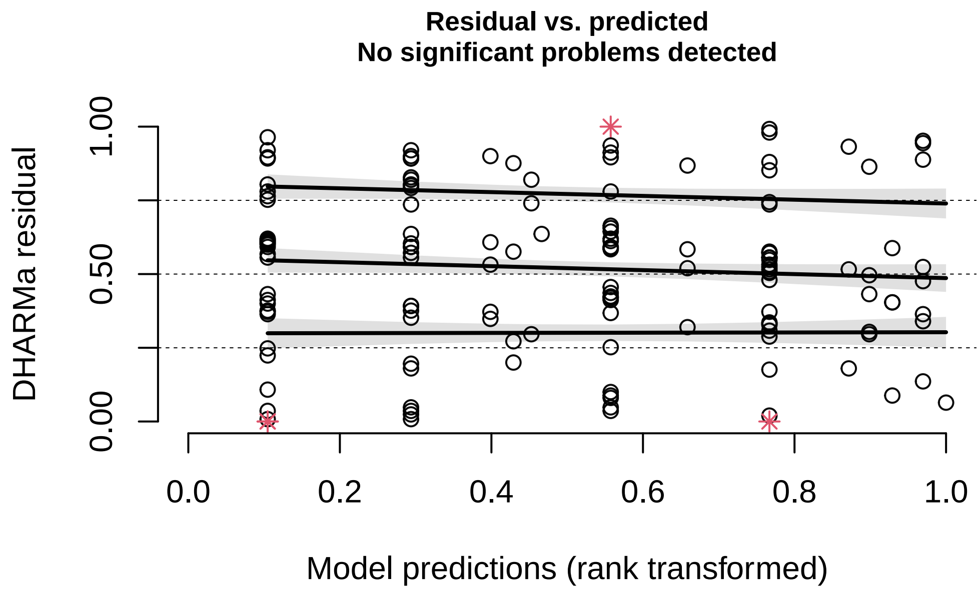
Lack of Linearity Independence of Residuals Normality of … Error Variance

```r
model2 <- prepost_num |>
  select(confidence_num, Year_Of_College, Gender,
         Time_Point, Simulation_Experience, Student_ID) |>
  drop_na()

# Make predictions using the fitted model
preds <- predict(confidence_model, newdata = model2)
```

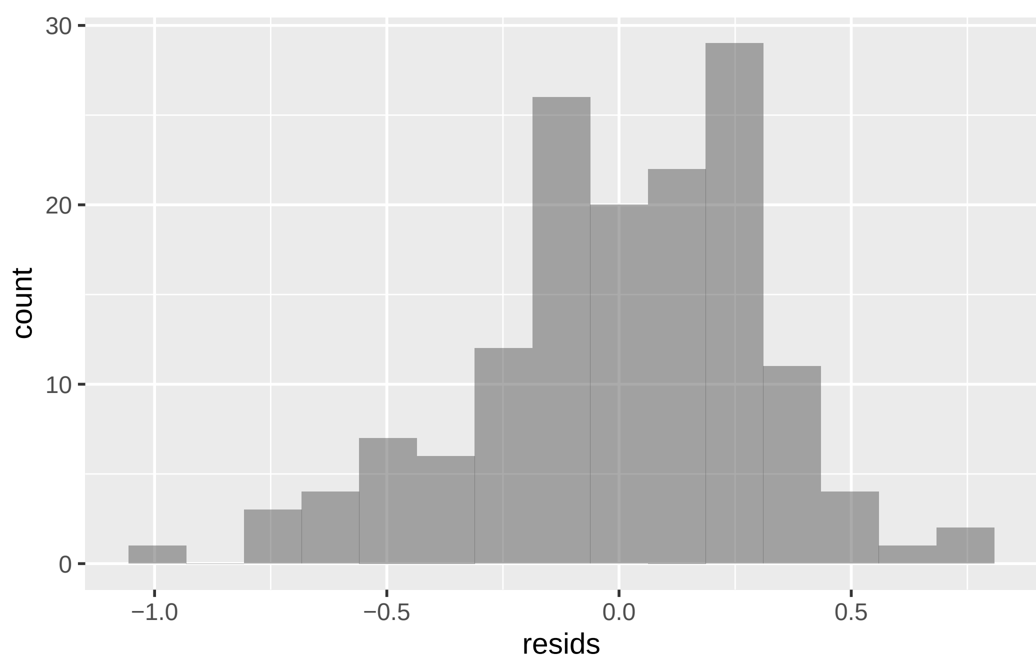
```r
# Calculate residuals
resids <- resid(confidence_model)

# Residuals vs. fitted values plot
gf_point(resids ~ preds, data = model2)
```



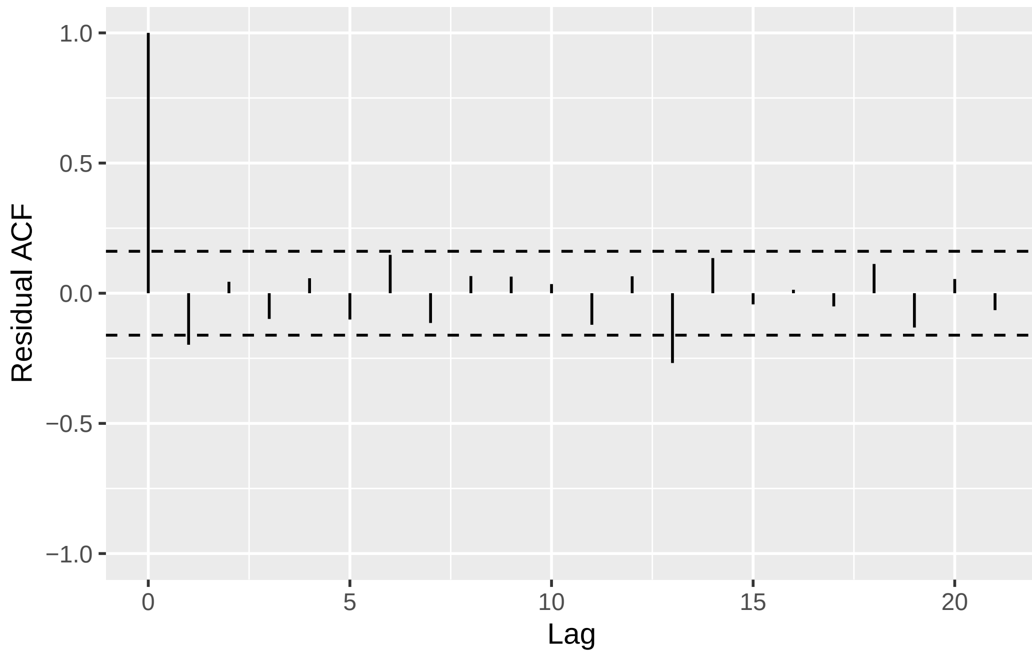

```r
# or alternately
plotResiduals(simulateResiduals(confidence_model))
```




```r
# Histogram of residuals
gf_histogram(~resids, data = model2, bins = 15)
```



```r
# ACF plot
s245::gf_acf(~ resids) |>  # Pass the correct formula here
  gf_lims(y = c(-1, 1))
```



Analysis of Confidence

Testing our assessments, it seems that all our assessments are able to pass. For Linearity, the scatterplot has no visible trends, which allows us to conclude that linearity passes. Our Histogram for the normality test also seems to pass here and although it seems to be right skewed, it is still seen as rather symmetric and normal. Our scatterplot point cloud also seems to fit well in a rectangle, which means that our error variance assessment passes. Finally, our ACF plot shows that there are two lag points that surpass the dotted lines (lag 1 and lag 13). However, these points do not surpass the dotted line by an exceeding amount, and taking into account that the majority of the other points lie within the dotted line, it can be said that the Independence test also passes. Since all tests pass, we are able to move on to model selection and draw conclusions for the confidence model.

Model Selection

Next, we are able to go on to Model Selection to further explore whether the main predictor plays a role in affecting student's confidence in health assessments and whether using time_point as an interaction played a difference in predicting the response.

```r
car::Anova(confidence_model)
```

```
Analysis of Deviance Table (Type II Wald chisquare tests)

Response: confidence_num
                                   Chisq Df          Pr(>Chisq)
Time_Point                       92.9501  2 <0.0000000000000002 ***
Simulation_Experience             0.0501  1              0.8229
Year_Of_College                   0.5822  1              0.4454
Gender                            0.3373  1              0.5614
Time_Point:Simulation_Experience  0.9107  2              0.6342
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
pairwise_time_point <- emmeans(confidence_model,
                         specs = ~Time_Point | Simulation_Experience)
pairs(pairwise_time_point)
```

```
Simulation_Experience = No Experience:
 contrast                 estimate     SE  df t.ratio p.value
 (Post-test) - (Pre-test)    0.475 0.0897 138   5.296  <.0001
 (Post-test) - Two_Month    -0.272 0.2158 138  -1.260  0.4204
 (Pre-test) - Two_Month     -0.747 0.2160 138  -3.458  0.0021

Simulation_Experience = Previous Experience:
 contrast                 estimate     SE  df t.ratio p.value
 (Post-test) - (Pre-test)    0.594 0.0870 138   6.831  <.0001
 (Post-test) - Two_Month    -0.234 0.1588 138  -1.472  0.3076
 (Pre-test) - Two_Month     -0.828 0.1584 138  -5.226  <.0001

Results are averaged over the levels of: Year_Of_College, Gender
P value adjustment: tukey method for comparing a family of 3 estimates
```

Analysis of Model Selection

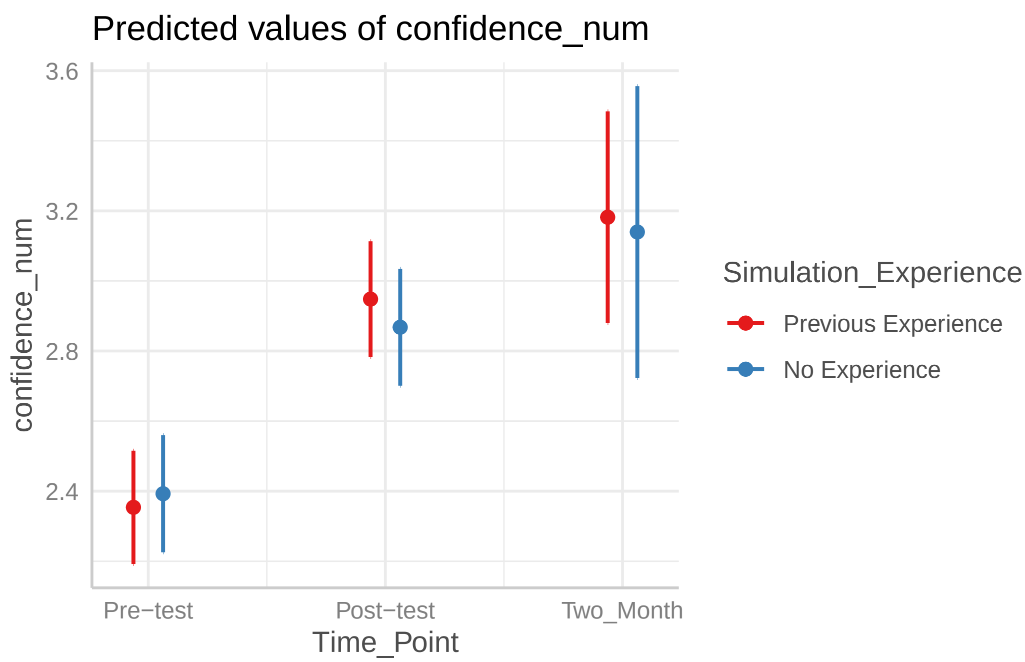
For Model Selection, I used the Anova table to explore whether my main predictor, Time_Point, had any evidence of affecting my response, the confidence of nurses in health assessments after VR_Experiences. Through analysis of p-values, we know that a p-value that is close to 0 evidently shows that the specific variable does play a role in affecting the response. In this case, my main predictor had a p-value score of 0.00000000003089, which is extremely close to 0 and we can therefore say that it affects our response. Nevertheless, all of our other predictor variables had large p-values, which lacks evidence that these variables affect my main response. As for our interaction with Simulation_Experience, the p-value is 0.2715. Because this is quite a large p-value, we fail to find enough evidence that this interaction affects our response as well.

Next, we used Hypothesis Testing, exploring how the different time_points differ from each other to further explore whether Time_Point affects our response and which comparison of time points specifically affected our response. First looking at (Post-test No Experience) - (Pre-test No Experience) comparison, we see a low p-value of 0.0016 and know that this comparison indicates a difference in confidence levels between nurses who had no previous VR experience and underwent assessments at the post-test stage compared to those assessed at the pre-test stage.

However, for this comaparison, (Post-test No Experience) - (Post-test Previous Experience), we have a p-value of 0.9961. This shows that there is no evidence that whether or not you have Simulation Experiences affects our main response, which further shows that our interaction, Simulation_Experience does not affect our response.

Prediction Plot

```
ggpredict(confidence_model,
          terms = c('Time_Point', 'Simulation_Experience'),
          type = 'fixed') |>
  plot()
```



Analysis of Prediction Plot

In this analysis, I used a model that looks at how previous VR experiences (Simulation_Experience) and time (Time_Point) work together to affect how confident nursing students feel about their health assessments, in which Time_Point is our main predictor. This fits our goal of seeing how VR experiences influence confidence over time.

Looking at the prediction plot, we see different patterns for students with and without VR experience as time goes on. Overall, comparing the time points, pre-test and post-test, it shows that immediately after the VR_Experience (post-test), students had a significantly higher confidence score. This signifies that time point definitely matters in our model analysis in which after experiencing a VR experience, confidence levels increase.

However, as for the interaction, Simulation_Experience, we are exploring whether time point working with previous simulation experiences also affected our response. However, according to our prediction plot, it shows that the prediction plot did not differ by a large scale for pre-test and post-test comparing people having simulation experiences and people who did not. There was quite a difference in the 2 months after having a VR nursing experience, however, Professor Kunnen was not very interested in the after 2 month test and she was more focused on how pre-test compared to post-test. Because of this, the prediction plot shows that there is not enough evidence that our interaction affected our response.

Conclusions

Key Findings

Question 2 Answer: When we looked at how nurses felt about health assessments, we found that their previous experiences with VR didn't seem to make a big difference in their confidence levels when we looked at the timing of assessments. But, the timing of assessments itself did matter. After nurses experienced VR, they generally felt more confident, especially right after the VR experience. Model Insights

Our analysis showed that the timing of assessments was really important for how confident nurses felt. Right after using VR, their confidence levels went up, which tells us that timing is key for boosting confidence. Implications

While VR experiences can make nurses feel more confident over time, having previous simulation experiences didn't seem to add much to their confidence levels. This means that focusing on when nurses take assessments might be more important for boosting their confidence in health assessments.