Data_analysis_all

June 2, 2023

1 Data Analysis - all data

In this notebook, we analyzed the combined data resulting from the three experiments conducted with the "**AR**ound the world" app in 3 schools in San Sebastian, Spain. The data includes both the raw data compiled from the app and the student surveys. There are two types of students based on the device they use during the experiment: users who used the app from a PC (they can see what other students do and provide suggestions, and replace AR content with 3D objects from a Three.js canvas) or mobile (users with a tablet or cellphone, they can also receive questions from the teacher and answer them).

After the trial, the students were given a survey consisting of a number of questions, which they had to rate from 1 to 5. There were 16 common questions, 2 questions phrased slightly differently for mobile/PC users, and 2 questions only for mobile users.

1.1 Student surveys

In this section we will analyse the student surveys that were completed after the experiment. This is the full list of questions:

1. I think that I would like to use the application frequently.
2. I found the application to be simple.
3. I thought the application was easy to use.
4. I think that I could use the application without the support of a technical person.
5. I found the various functions in the application were well integrated
6. I would imagine that most people would learn to use the application very quickly.
7. I found the application very intuitive.
8. I felt very confident using the application.
9. I could use the application without having to learn anything new.
10. I would like to use the application during a test
11. Being able to provide suggestions made me feel more involved
12. Receiving suggestions made me more confident when answering a question
13. At all times I have been able to understand what the person who had to respond to the exercise was doing
14. I find it more interesting to solve the exercises through the application than through a web page or in writing
15. Suggestions from my classmates have helped me when answering the exercise
16. The device used has allowed me to use the application easily
17. I would like to use the application to learn new concepts
18. Being able to use augmented reality / 3D elements makes the application more entertaining

19. There are several ways to collaborate with my classmates through the application
20. Thanks to augmented reality / 3D elements I have felt immersed in the learning activity

Questions #12 and #15 only appeared in the questionnaires filled by students using a mobile device, since students on a PC did not have the possibility to answer questions through the app or receive suggestions.

The 2 questions phrased differently are #18 and #20, where the words "augmented reality" were used in the questionnaires filled by the students using a mobile device, and "3D elements" in case of students on PC.

[1]:
```
# If you want to use help from chatGPT, uncomment the following line
%load_ext ask_ai.magics
# make sure that you have stored your OpenAI API key in the variable␣
↪OPENAI_API_KEY
```

[2]:
```
# And import the necessary libraries. xapi_analysis is the package we created␣
↪to help analysing xapi statements
from xapi_analysis.input_csv import *
import numpy as np
import pandas as pd
import seaborn as sns
from pathlib import Path
from typing import Set, List, Union
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker

# Let's also set some useful display constants for pandas
pd.options.display.max_columns = 500
pd.options.display.max_rows = 500
pd.options.display.max_colwidth = 500

# And something for plotting better images, too.
plt.rcParams['figure.figsize'] = [16,9]
plt.rcParams['axes.titlesize'] = 18     # fontsize of the axes title
plt.rcParams['axes.labelsize'] = 14    # fontsize of the x and y labels
plt.rcParams['xtick.labelsize'] = 13    # fontsize of the tick labels
plt.rcParams['ytick.labelsize'] = 13    # fontsize of the tick labels
plt.rcParams['legend.fontsize'] = 13    # legend fontsize
plt.rcParams['font.size'] = 13
cmap_cont = sns.color_palette('crest', as_cmap=True)
cmap_disc = sns.color_palette('RdYlBu_r')
```

[3]:
```
SURVEY_FILE = Path('./questionnaire_answers.xlsx')
SHEET_NAMES = ['SALESIANOS', 'ZUBIRI_MANTEO', 'DEUSTO'] # orderd by age
NUM_ROWS = 22
COLS = [list(range(4, 21)), list(range(4, 21)), list(range(4, 14))]
```

```
frames = []
for idx, s in enumerate(SHEET_NAMES):
    frames.append(pd.read_excel(SURVEY_FILE, sheet_name=SHEET_NAMES[idx],␣
 ↪nrows=NUM_ROWS, usecols=COLS[idx]))

survey_answers = pd.concat(frames, axis=1)
survey_answers.index += 1 # so index value is the same as the question number
survey_answers = survey_answers.astype('Int64')

questions = pd.read_excel(SURVEY_FILE, sheet_name=SHEET_NAMES[0],␣
 ↪nrows=NUM_ROWS, usecols=[2])
questions.index += 1 # so index value is the same as the question number

q_type = pd.read_excel(SURVEY_FILE, sheet_name=SHEET_NAMES[0], nrows=NUM_ROWS,␣
 ↪usecols=[3])
q_type.index += 1
```

Let's have a quick look at the data

[4]:
```
survey_answers.head()
```

[4]:
```
   iPad1  iPad2  Tablet1  Tablet2  iPhone1  Android1  Android2  Android3  \
1      3      3        4        5        3         5         4         3
2      4      4        5        4        3         2         3         3
3      4      3        4        4        3         4         3         3
4      5      4        3        4        5         4         2         2
5      5      4        4        4        3         5         4         3

   Android4  PC002  PC003  PC004  PC005  PC006  PC007  PC008  PC009  iPad202  \
1         3      3      3      3      3      1      4      3      4        3
2         3      4      4      4      3      2      4      4      5        5
3         4      5      4      3      2      1      4      4      5        5
4         4      5      4      4      4      1      3      4      5        5
5         3      4      4      4      4      2      3      4      5        4

   Tablet201  Tablet202  iPhone201  iPhone202  Android201  Android202  \
1          3          4          4          3           5           1
2          4          5          5          5           5           4
3          4          5          5          5           5           4
4          4          5          4          5           5           5
5          3          3          4          4           4           3

   Android203  Android204  PC021  PC022  PC023  PC024  PC025  PC026  PC028  \
1           4           4      5      3      1      4      3      5      4
2           4           5      4      3      5      5      2      3      5
3           4           5      5      2      5      5      5      5      5
4           5           5      5      3      5      5      2      4      4
```

```
5          5          5      5      4      4      5      4      5      4

   PC029  iPad101  Tablet101  Tablet102  iPhone101  iPhone102  Android101  \
1      5        4          3          4          4          4           3
2      4        5          4          4          4          5           4
3      4        4          4          4          4          4           3
4      3        3          4          4          4          4           3
5      3        4          4          4          4          4           2

   Android102  Android103  Android104  PC010
1           4           4           3      1
2           4           5           3      3
3           4           4           4      4
4           5           3           3      4
5           4           4           5      3
```

[5]:
```
survey_answers.describe()
```

[5]:
```
          iPad1     iPad2   Tablet1   Tablet2   iPhone1  Android1  Android2  \
count   20.0000  20.00000  20.00000  20.00000  20.00000  20.00000  20.00000
```

```
          iPad1     iPad2   Tablet1   Tablet2   iPhone1  Android1  Android2
count      20.0      20.0      20.0      20.0      20.0      20.0      20.0  \
mean       4.15       4.0       4.2       3.9       3.6       3.9       3.7
std     0.67082  0.794719  0.695852  0.718185  0.940325  1.020836  1.031095
min         3.0       2.0       3.0       2.0       2.0       2.0       2.0
25%         4.0       4.0       4.0       4.0       3.0       3.0       3.0
50%         4.0       4.0       4.0       4.0       3.5       4.0       4.0
75%         5.0      4.25       5.0       4.0       4.0       5.0      4.25
max         5.0       5.0       5.0       5.0       5.0       5.0       5.0

       Android3  Android4     PC002     PC003     PC004     PC005     PC006
count      20.0      20.0      18.0      18.0      18.0      18.0      18.0  \
mean       3.35      3.65  4.055556  4.222222  4.055556  3.833333  2.333333
std     0.67082  0.933302  0.872604  0.732084  1.055642  0.857493  1.084652
min         2.0       2.0       2.0       3.0       1.0       2.0       1.0
25%         3.0       3.0       4.0       4.0       4.0       3.0       2.0
50%         3.0       4.0       4.0       4.0       4.0       4.0       2.0
75%         4.0       4.0       5.0       5.0       5.0       4.0       3.0
max         4.0       5.0       5.0       5.0       5.0       5.0       5.0

          PC007     PC008     PC009   iPad202  Tablet201  Tablet202
count      18.0      18.0      18.0      20.0       20.0       20.0  \
mean   3.888889  4.222222  4.777778       4.4       3.35        3.7
std     1.02262  0.548319  0.427793  0.820783    1.03999   1.174286
min         2.0       3.0       4.0       3.0        1.0        2.0
25%         3.0       4.0       5.0       4.0        3.0       2.75
50%         4.0       4.0       5.0       5.0        3.5        4.0
75%         5.0      4.75       5.0       5.0        4.0        5.0
max         5.0       5.0       5.0       5.0        5.0        5.0
```

```
       iPhone201  iPhone202  Android201  Android202  Android203  Android204  
count       20.0       20.0        20.0        20.0        20.0        20.0   \
mean         4.4        4.3         4.4        2.75         4.5         4.8   
std     0.502625   0.656947    0.680557    1.585294    0.688247    0.410391   
min          4.0        3.0         3.0         1.0         3.0         4.0   
25%          4.0        4.0         4.0         1.0         4.0         5.0   
50%          4.0        4.0         4.5         3.0         5.0         5.0   
75%          5.0        5.0         5.0         4.0         5.0         5.0   
max          5.0        5.0         5.0         5.0         5.0         5.0   

          PC021     PC022     PC023     PC024     PC025     PC026     PC028  
count      18.0      18.0      18.0      18.0      18.0      18.0      18.0   \
mean   4.833333  3.944444  4.666667  4.777778  3.611111  4.333333  4.555556   
std    0.383482  0.872604  0.970143  0.427793  1.092159  0.766965   0.51131   
min         4.0       2.0       1.0       4.0       2.0       3.0       4.0   
25%         5.0      3.25       5.0       5.0       3.0       4.0       4.0   
50%         5.0       4.0       5.0       5.0       4.0       4.5       5.0   
75%         5.0      4.75       5.0       5.0       4.0       5.0       5.0   
max         5.0       5.0       5.0       5.0       5.0       5.0       5.0   

          PC029    iPad101  Tablet101  Tablet102  iPhone101  iPhone102  
count      18.0       20.0       20.0       20.0       20.0       20.0   \
mean   3.722222        4.0        3.9        4.1        3.7        4.4   
std    0.751904   0.648886   0.640723   0.552506   0.864505   0.820783   
min         2.0        3.0        3.0        3.0        2.0        2.0   
25%         3.0        4.0       3.75        4.0        3.0        4.0   
50%         4.0        4.0        4.0        4.0        4.0        5.0   
75%         4.0        4.0        4.0        4.0        4.0        5.0   
max         5.0        5.0        5.0        5.0        5.0        5.0   

       Android101  Android102  Android103  Android104     PC010  
count        20.0        20.0        20.0        20.0      18.0  
mean          3.1         4.4        4.25        3.75  2.666667  
std      0.718185    0.502625    0.638666    0.966546  1.283378  
min           2.0         4.0         3.0         2.0       1.0  
25%           3.0         4.0         4.0         3.0      1.25  
50%           3.0         4.0         4.0         4.0       3.0  
75%           4.0         5.0         5.0        4.25       4.0  
max           4.0         5.0         5.0         5.0       4.0  
```

We also classified questions into four different groups (**Collaboration**, **Functionality**, **Usability**, **Educational**). Let's specify which questions belong to each group

[6]:
```
collab = [1, 11, 12, 13, 15, 19]
functi = [5]
usabil = [2, 3, 4, 6, 7, 8, 9, 16]
```

```
educat = [10, 14, 17, 18, 20]
```

Before we plot the distribution of the answers per question, we need to sum the answers. We will have a new dataframe, with one row per question, and in the columns the percentage of answer in each category (**Strongly disagree**, **Disagree**, **Neutral**, **Agree**, **Strongly agree**)

[7]:
```
df = survey_answers.apply(pd.Series.value_counts, axis=1)[[1, 2, 3, 4, 5]].
    ↪fillna(0)
df.columns = ['SD', 'D', 'N', 'A', 'SA']
df.head()
```

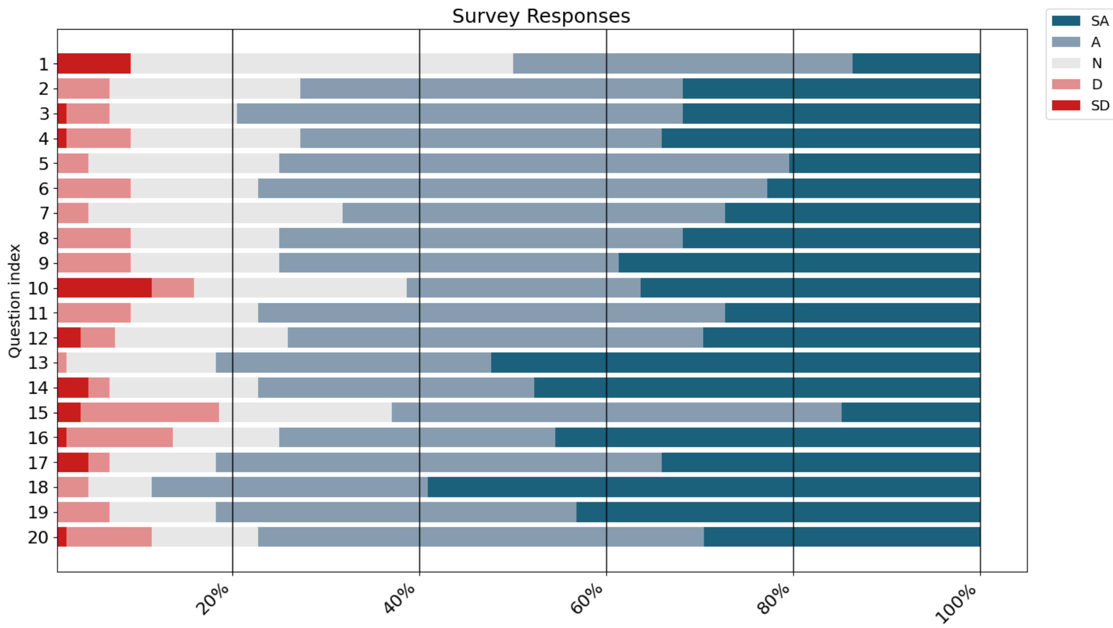
[7]:

	SD	D	N	A	SA
1	4	0	18	16	6
2	0	3	9	18	14
3	1	2	6	21	14
4	1	3	8	17	15
5	0	2	9	24	9

[10]:
```
def stacked_barplot_100(df: Union[pd.DataFrame, pd.Series], # input dataframe
                        title: str=None,  # title of the plot,
                        q_idx: List=None  # index of questions
                        ):
    """
    Creates a 100% stacked bar plot to visualize the answers of the student␣
  ↪survey.
    The input dataframe MUST have the columns SD, D, N, A, SA which represents␣
  ↪the number of answers
    to a specific value in the Likert scale
    """
    ax = plt.gca()

    ind = [x for x, _ in enumerate(df.index)]

    if q_idx is not None:
        df['Question_idx'] = q_idx
    else:
        df['Question_idx'] = list(range(1,21))
    df = df.sort_values(['Question_idx'], ascending=False)

    strongdisagree = df.SD
    disagree = df.D
    neutral = df.N
    agree = df.A
    strongagree = df.SA

    #calculate the percentages for the 100% stacked bars
    total = strongdisagree+disagree+neutral+agree+strongagree
```

```
    prop_strongdisagree = np.true_divide(strongdisagree, total) * 100
    prop_disagree = np.true_divide(disagree, total) * 100
    prop_neutral = np.true_divide(neutral, total) * 100
    prop_agree = np.true_divide(agree, total) * 100
    prop_strongagree = np.true_divide(strongagree, total) * 100

    #plot the bars
    ax.barh(ind, prop_strongagree, label='SA', color='#1b617b',
             left=prop_strongdisagree+prop_disagree+prop_neutral+prop_agree)
    ax.barh(ind, prop_agree, label='A', color='#879caf',
             left=prop_strongdisagree+prop_disagree+prop_neutral)
    ax.barh(ind, prop_neutral, label='N', color='#e7e7e7',␣
↪left=prop_strongdisagree+prop_disagree)
    ax.barh(ind, prop_disagree, label='D', color='#e28e8e',␣
↪left=prop_strongdisagree)
    ax.barh(ind, prop_strongdisagree, label='SD', color='#c71d1d')

    #set the axes
    plt.yticks(ind, df.index)
    plt.ylabel("Question index")
    plt.title(title)
    plt.legend(bbox_to_anchor=(1.1, 1.05))
    plt.xlim(1.2)

    #fine tune the labels
    plt.setp(ax.get_xticklabels(), rotation=45, horizontalalignment='right')
    ax.grid(color='black', linestyle='-', axis="x", linewidth=1)
    ax.set_facecolor('white')
    ax.xaxis.set_major_formatter(ticker.FuncFormatter(lambda x, pos: '{:,.0f}'.
↪format(x) + '%'))
    plt.tick_params(labelsize=16)

    plt.show()
```

[11]:
```
stacked_barplot_100(df, "Survey Responses")
```



It seems that the majority of users answered **agree** or **strongly agree** to all the questions. Let's have a look at the dataset with the percentages, too:

[12]:
```
cols=['SA','A','N','D','SD']
df[cols] = df[cols].div(df[cols].sum(axis=1), axis=0).multiply(100)

df[cols] = df[cols].round(2)
df.insert(loc=0, column='Question', value=questions)
df = df.sort_values(['Question_idx'], ascending=True)
df.drop('Question_idx', axis=1)
```

[12]:
```
                                   Question
1                                                            I think that I would like
to use the application frequently.  \
2                                                                                   I
found the application to be simple.
3                                                                              I
thought the application was easy to use.
4                               I think that I could use the application without
the support of a technical person.
5                                             I found the various functions in
the application were well integrated
6                                 I would imagine that most people would learn
to use the application very quickly.
7                                                                                 I
found the application very intuitive.
8                                                                          I felt
```

very confident using the application.
9 I could use the application without having to learn anything new.
10 I would like to use the application during a test
11 Being able to provide suggestions made me feel more involved
12 Receiving suggestions made me more confident when answering a question
13 At all times I have been able to understand what the person who had to respond to the exercise was doing
14 I find it more interesting to solve the exercises through the application than through a web page or in writing
15 Suggestions from my classmates have helped me when answering the exercise
16 The device used has allowed me to use the application easily
17 I would like to use the application to learn new concepts
18 Being able to use augmented reality / 3D elements makes the application more entertaining
19 There are several ways to collaborate with my classmates through the application
20 Thanks to augmented reality / 3D elements I have felt immersed in the learning activity

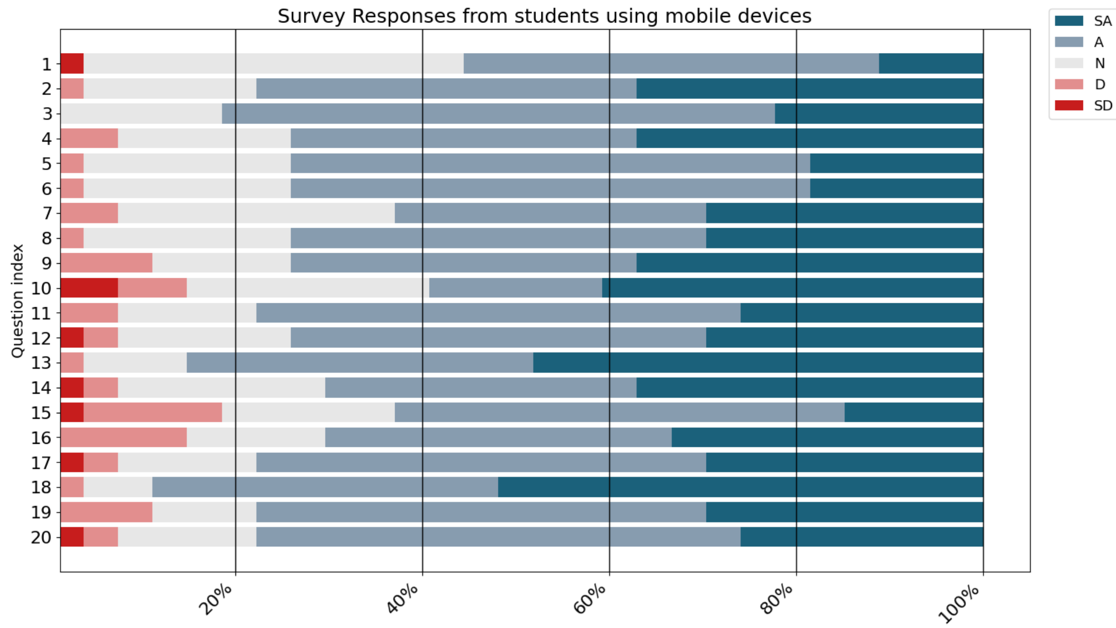
	SD	D	N	A	SA
1	9.09	0.0	40.91	36.36	13.64
2	0.0	6.82	20.45	40.91	31.82
3	2.27	4.55	13.64	47.73	31.82
4	2.27	6.82	18.18	38.64	34.09
5	0.0	4.55	20.45	54.55	20.45
6	0.0	9.09	13.64	54.55	22.73
7	0.0	4.55	27.27	40.91	27.27
8	0.0	9.09	15.91	43.18	31.82
9	0.0	9.09	15.91	36.36	38.64
10	11.36	4.55	22.73	25.0	36.36
11	0.0	9.09	13.64	50.0	27.27
12	3.7	3.7	18.52	44.44	29.63
13	0.0	2.27	15.91	29.55	52.27
14	4.55	2.27	15.91	29.55	47.73
15	3.7	14.81	18.52	48.15	14.81
16	2.27	11.36	11.36	29.55	45.45
17	4.55	2.27	11.36	47.73	34.09
18	0.0	4.55	6.82	29.55	59.09
19	0.0	6.82	11.36	38.64	43.18
20	2.27	9.09	11.36	47.73	29.55

Now we will repeat the same analysis, but with the results split in several ways:

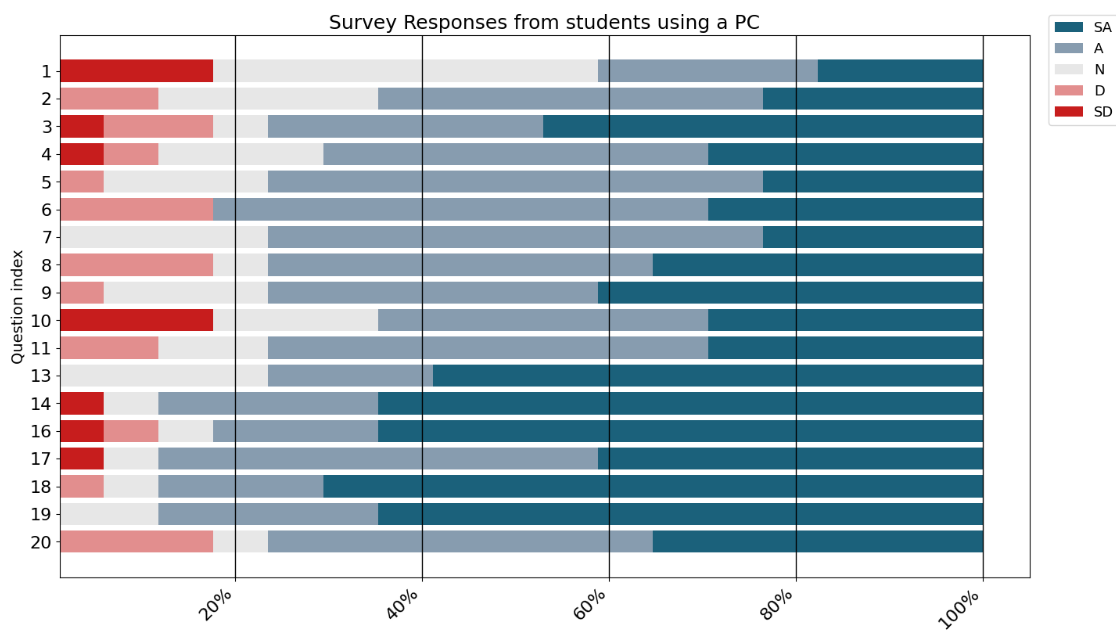
- By school / age group
- By role (active user vs. suggestions only)
- By question type

[13]:
```
group_14_yrs = survey_answers.iloc[:, 1:17]
group_17_yrs = survey_answers.iloc[:, 27:44]
group_19_yrs = survey_answers.iloc[:, 17:27]

group_active = survey_answers[survey_answers.columns.drop(list(survey_answers.
 ↪filter(regex='PC')))]
group_watchers = survey_answers.filter(like='PC').drop(index=[12, 15]) # the␣
 ↪questions only for active users

group_collab = survey_answers.filter(items=collab, axis=0)
group_functi = survey_answers.filter(items=functi, axis=0)
group_educat = survey_answers.filter(items=educat, axis=0)
group_usabil = survey_answers.filter(items=usabil, axis=0)
```

[14]:
```
df_active = group_active.apply(pd.Series.value_counts, axis=1)[[1, 2, 3, 4, 5]].
 ↪fillna(0)
df_active.columns = ['SD', 'D', 'N', 'A', 'SA']
df_watchers = group_watchers.apply(pd.Series.value_counts, axis=1)[[1, 2, 3, 4,␣
 ↪5]].fillna(0)
df_watchers.columns = ['SD', 'D', 'N', 'A', 'SA']
q_idx_watchers = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 16, 17, 18, 19, 20]

stacked_barplot_100(df_active, "Survey Responses from students using mobile␣
 ↪devices")
```



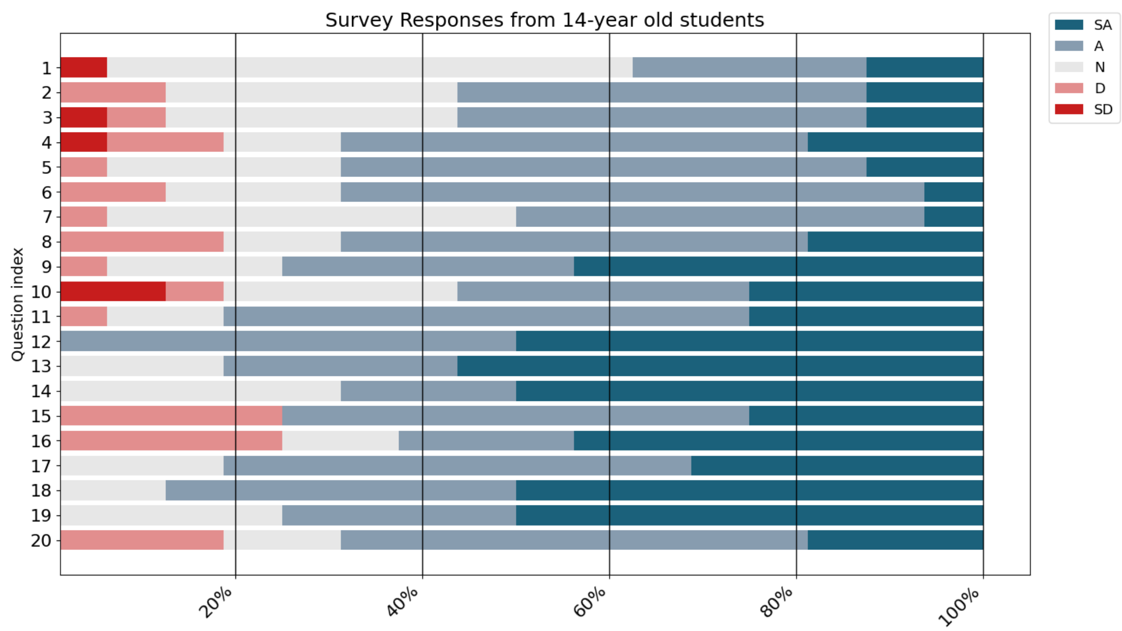
[15]:
```
stacked_barplot_100(df_watchers, "Survey Responses from students using a PC",␣
↪q_idx_watchers)
```



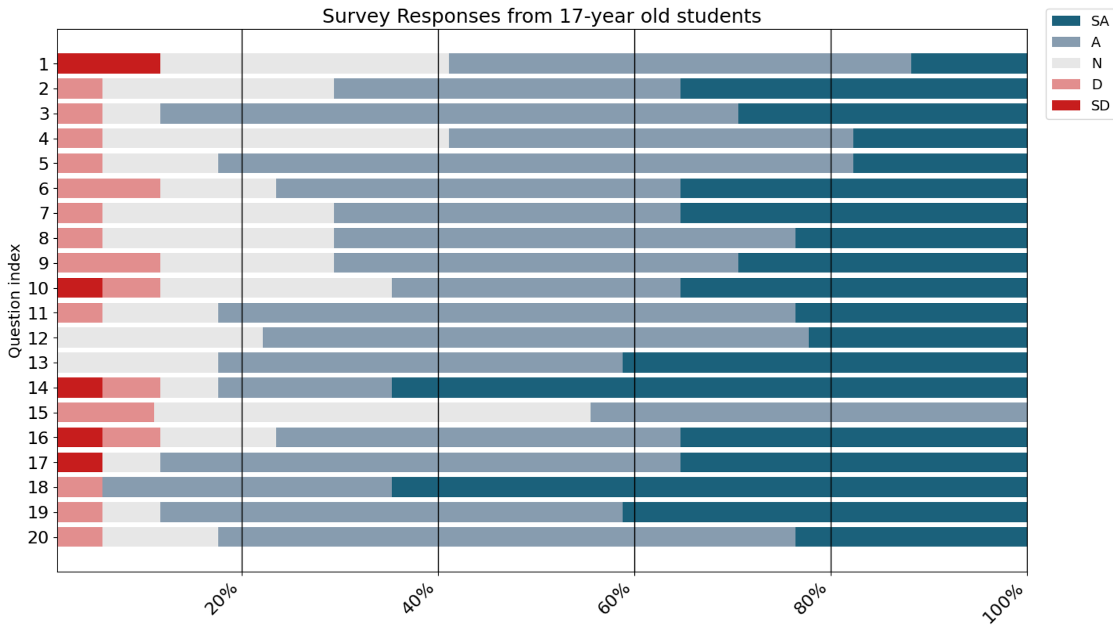
For the users on a PC the questions 12 and 15 are missing, since these question did not appear in their questionnaire. While the trend is similar, it looks like that active users (the ones using a mobile device and experiencing AR content) answered in a slightly more positive fashion. We will have a clearer idea when plotting the mean answer.

Now, repeat the process for the other groups. First we plot by school:

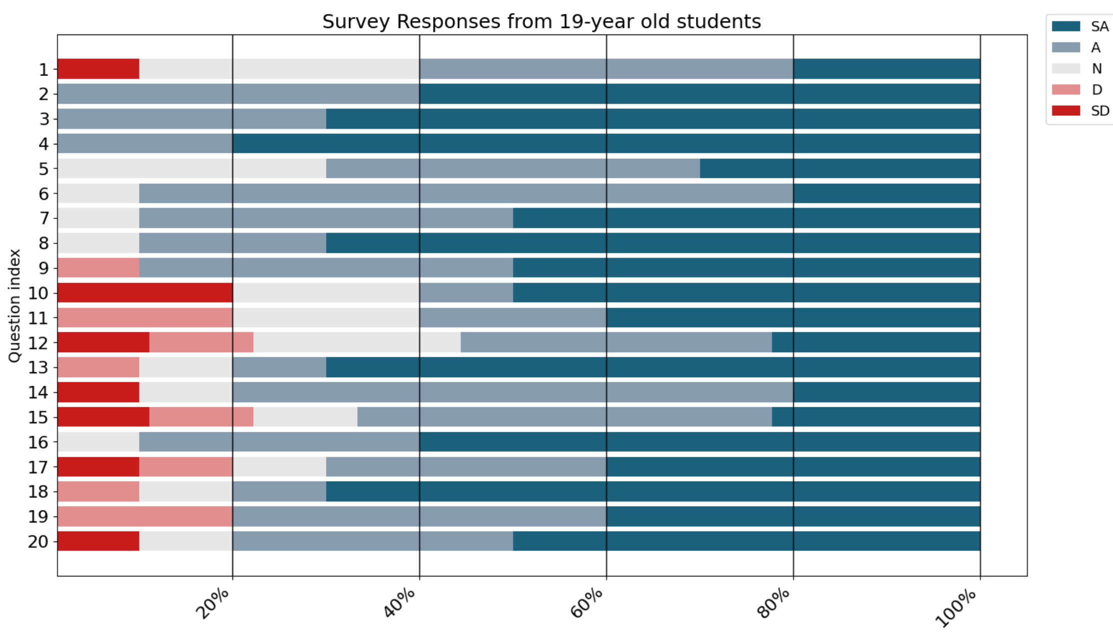
[16]:
```
df_14yrs = group_14_yrs.apply(pd.Series.value_counts, axis=1)[[1, 2, 3, 4, 5]].
  ↪fillna(0)
df_14yrs.columns = ['SD', 'D', 'N', 'A', 'SA']
df_17yrs = group_17_yrs.apply(pd.Series.value_counts, axis=1)[[1, 2, 3, 4, 5]].
  ↪fillna(0)
df_17yrs.columns = ['SD', 'D', 'N', 'A', 'SA']
df_19yrs = group_19_yrs.apply(pd.Series.value_counts, axis=1)[[1, 2, 3, 4, 5]].
  ↪fillna(0)
df_19yrs.columns = ['SD', 'D', 'N', 'A', 'SA']

stacked_barplot_100(df_14yrs, "Survey Responses from 14-year old students")
```



[17]:
```
stacked_barplot_100(df_17yrs, "Survey Responses from 17-year old students")
```



[18]:
```
stacked_barplot_100(df_19yrs, "Survey Responses from 19-year old students")
```

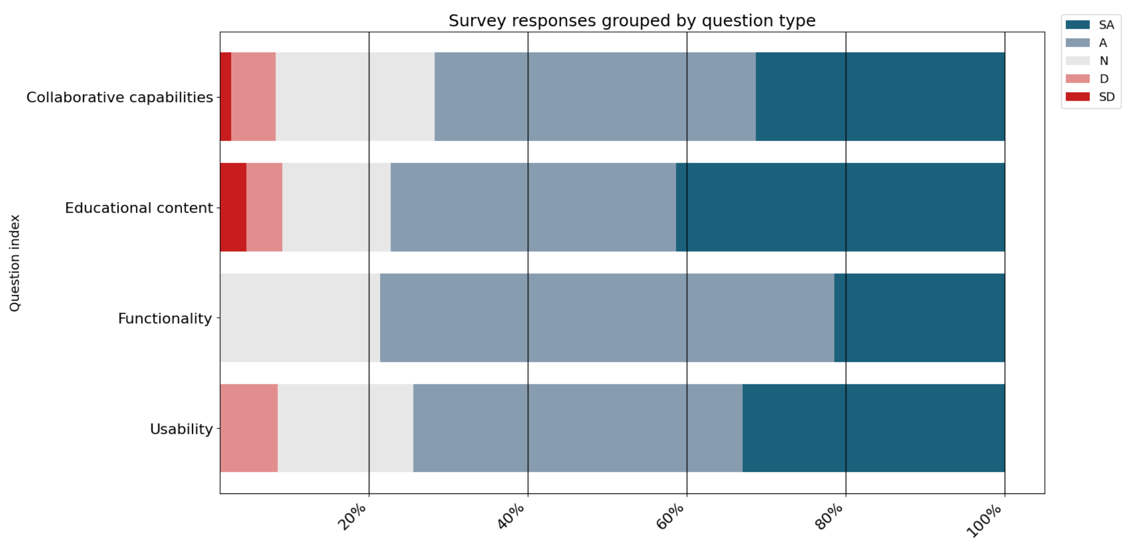


Again, while the trend is similar, it seems that younger students enjoyed the application more.

Let's check now the results but split by question type. In this case we have filtered the data by row, so we group the results like before, but then we sum over the columns to get the aggregated results per question type:

[19]:

```
df_tmp = group_collab.apply(pd.Series.value_counts, axis=1)[[1, 2, 3, 4, 5]].
 ↪fillna(0)
df_tmp.columns = ['SD', 'D', 'N', 'A', 'SA']
s_collab = df_tmp.sum(axis=0)

df_tmp = group_functi.apply(pd.Series.value_counts, axis=1)[[3, 4, 5]].fillna(0)
df_tmp.columns = ['N', 'A', 'SA']
s_functi = df_tmp.sum(axis=0)
s_functi['SD'] = 0
s_functi['D'] = 0

df_tmp = group_educat.apply(pd.Series.value_counts, axis=1)[[1, 2, 3, 4, 5]].
 ↪fillna(0)
df_tmp.columns = ['SD', 'D', 'N', 'A', 'SA']
s_educat = df_tmp.sum(axis=0)

df_tmp = group_usabil.apply(pd.Series.value_counts, axis=1)[[1, 2, 3, 4, 5]].
 ↪fillna(0)
df_tmp.columns = ['SD', 'D', 'N', 'A', 'SA']
s_usabil = df_tmp.sum(axis=0)

df_q_types = pd.concat([s_collab, s_functi, s_educat, s_usabil], axis=1).
 ↪transpose()
df_q_types.index = ['Collaborative capabilities', 'Functionality', 'Educational␣
 ↪content', 'Usability']
df_q_types

stacked_barplot_100(df_q_types, "Survey responses grouped by question type",␣
 ↪df_q_types.index)
```



Let's now quickly analyse the mean and standard deviation of the score obtained per answer.

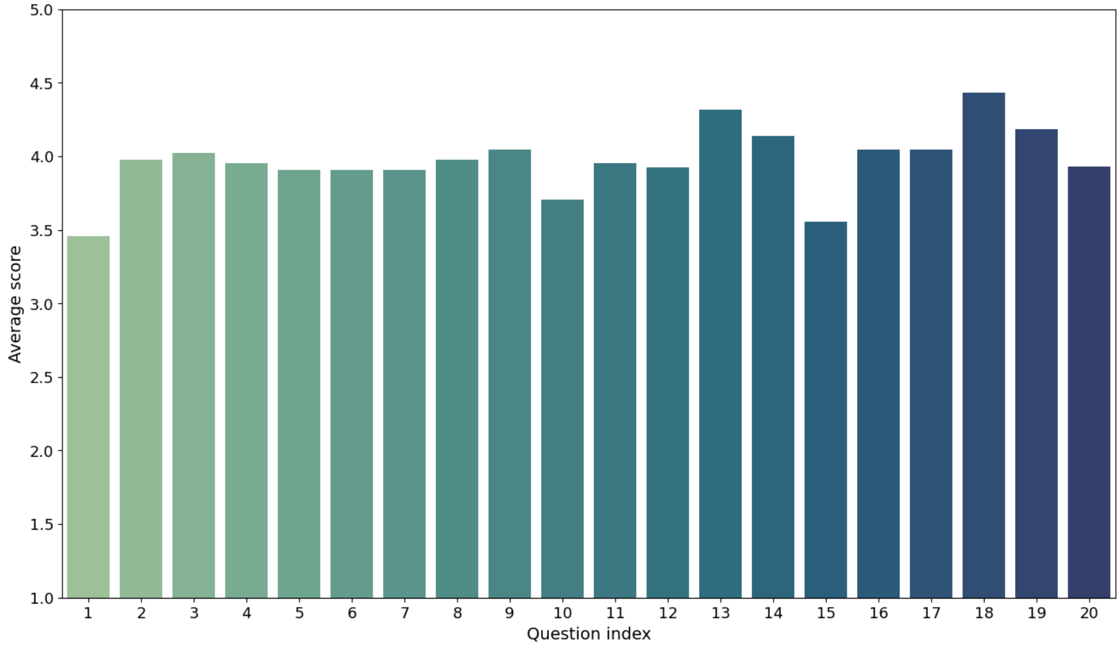
[20]:
```
tmp = pd.DataFrame(columns=['Type', 'Mean', 'Sd', 'Idx'])
tmp['Type'] = q_type
tmp['Mean'] = survey_answers.mean(numeric_only=True, axis=1)
tmp['Sd'] = survey_answers.std(numeric_only=True, axis=1)
tmp['Idx'] = list(range(1,21))
questions_avg_std = tmp[["Idx", "Mean", "Sd", "Type"]]
questions_avg_std
```

[20]:

	Idx	Mean	Sd	Type
1	1	3.454545	1.044466	Collaboration
2	2	3.977273	0.901901	Usability
3	3	4.022727	0.927328	Usability
4	4	3.954545	1.010516	Usability
5	5	3.909091	0.772136	Functionality
6	6	3.909091	0.857747	Usability
7	7	3.909091	0.857747	Usability
8	8	3.977273	0.927328	Usability
9	9	4.045455	0.963389	Usability
10	10	3.704545	1.322076	Education
11	11	3.954545	0.888022	Collaboration
12	12	3.925926	0.997147	Collaboration
13	13	4.318182	0.828917	Collaboration
14	14	4.136364	1.069469	Education
15	15	3.555556	1.050031	Collaboration
16	16	4.045455	1.119687	Usability
17	17	4.045455	0.987234	Education
18	18	4.431818	0.818329	Education
19	19	4.181818	0.896316	Collaboration
20	20	3.931818	0.997619	Education

[21]:
```
colors = [cmap_cont(i) for i in np.linspace(0, 1, len(questions_avg_std))]
sns.barplot(data=questions_avg_std, y='Mean', x='Idx', orient='v',␣
↪palette='crest')
plt.ylabel("Average score")
plt.xlabel("Question index")
plt.ylim(1,5)
```

[21]: (1.0, 5.0)



It is more interesting to analyze how the data are different for different groups of users. We will now plot the mean values, but differentiating the results per age and per device used. For this, we will now create a dataframe which is the transpose of the original (that is, each row contains the answers from a student and each column represents a question) and we add some new column such as age, device type, role in the test (active or watcher)

[22]:
```
survey_new = survey_answers.transpose()
survey_new.columns = ['Q'+str(c) for c in list(survey_new.columns.values)]

survey_new['Mean'] = survey_new.mean(axis=1)
```

[23]:
```
age = ['14 year-old'] * 17 + ['17 year-old'] * 17 + ['19 year-old'] * 10
survey_new["Age"] = age

def rem_digit(s):
    return "".join(filter(lambda x: not x.isdigit(), s))

survey_new["Device"] = survey_new.apply(lambda row: rem_digit(row.name), axis=1)

def set_user_type(s):
    if s.startswith(("PC")):
        return 'Watcher'
    else:
        return 'Active'
```

```python
survey_new["User type"] = survey_new.apply(lambda row: set_user_type(row.
    ↪Device), axis=1)
survey_new.head(3)
```

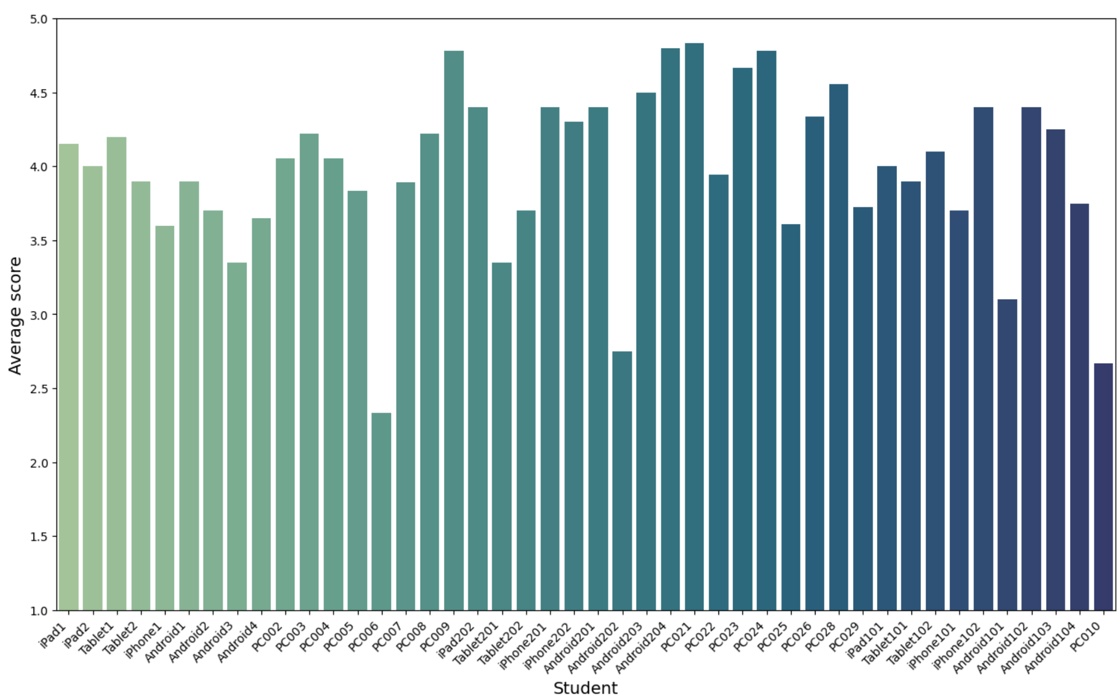
[23]:

```
         Q1  Q2  Q3  Q4  Q5  Q6  Q7  Q8  Q9  Q10  Q11  Q12  Q13  Q14  Q15  \
iPad1     3   4   4   5   5   5   4   4   3    5    4    3    4    4    4
iPad2     3   4   3   4   4   4   4   3   4    2    4    4    4    5    4
Tablet1   4   5   4   3   4   3   4   4   5    5    4    5    5    3    4

         Q16  Q17  Q18  Q19  Q20  Mean          Age  Device User type
iPad1      5    4    4    4    5  4.15  14 year-old    iPad    Active
iPad2      5    5    5    5    4  4.00  14 year-old    iPad    Active
Tablet1    4    4    5    5    4  4.20  14 year-old  Tablet    Active
```

Let's plot the average score per user, and then split the results according to different groups:

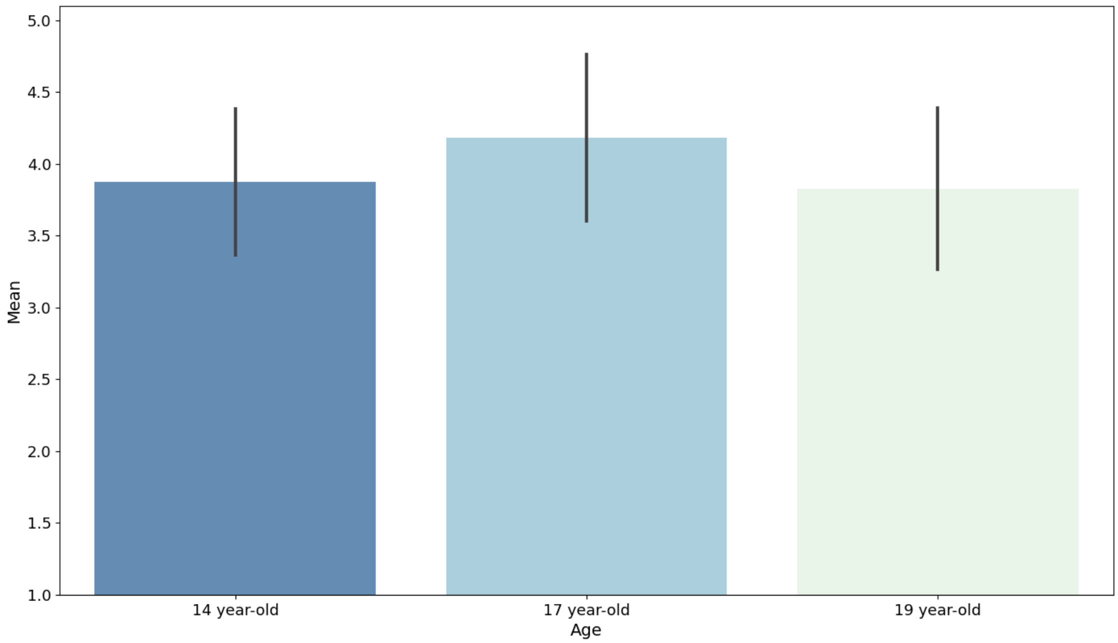
[24]:

```python
colors = [cmap_cont(i) for i in np.linspace(0, 1, len(survey_new.index))]
sns.barplot(data=survey_new, y='Mean', x=survey_new.index, orient='v',␣
    ↪palette='crest')
plt.ylabel("Average score")
plt.xlabel("Student")
plt.ylim(1,5)
ax = plt.gca()
plt.setp(ax.get_xticklabels(), rotation=45, horizontalalignment='right')
ax.set_facecolor('white')
plt.tick_params(labelsize=10)
```



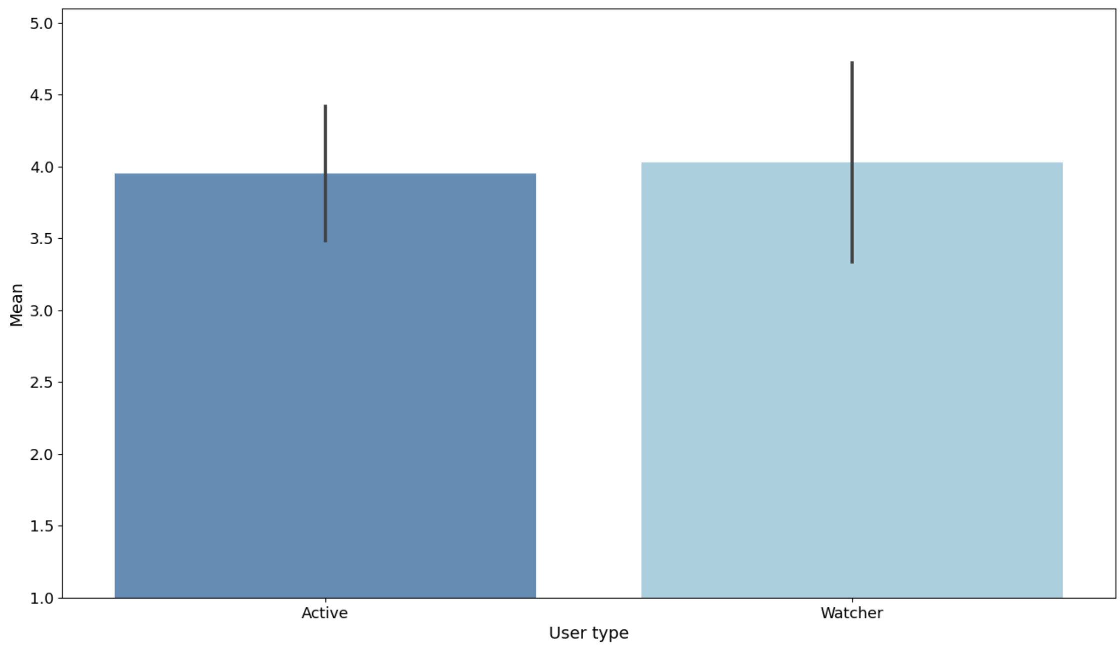
[25]:
```
g = sns.barplot(data=survey_new, y="Mean", x="Age", errorbar='sd',
                orient='v', palette=cmap_disc)
g.set(ylim=(1,5.1))
```

[25]: [(1.0, 5.1)]



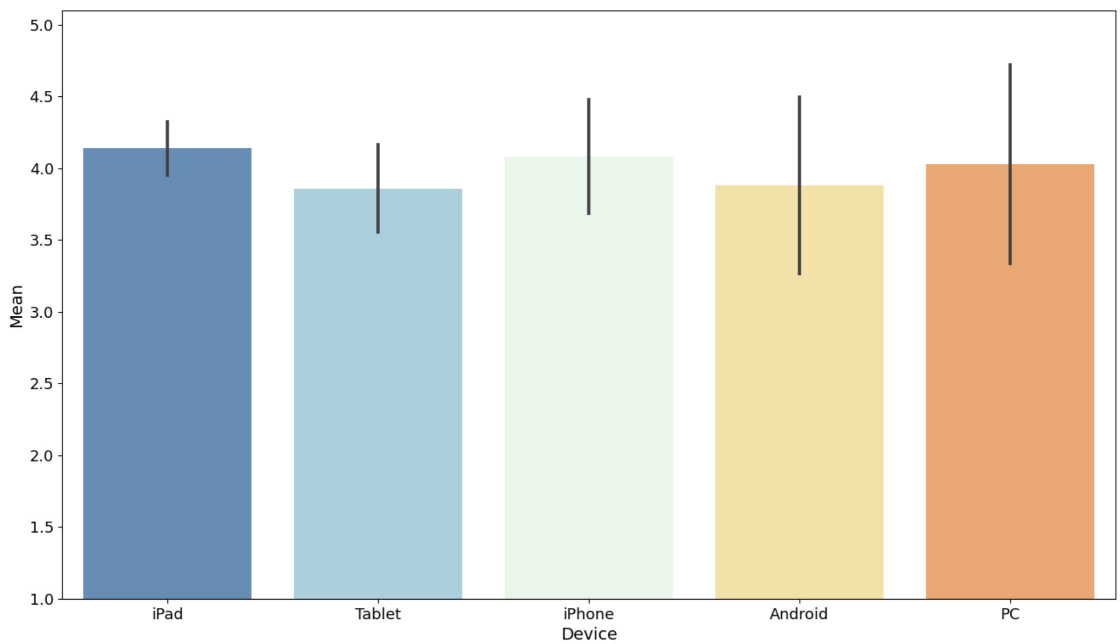
[26]:
```
g = sns.barplot(data=survey_new, y="Mean", x="User type", errorbar='sd',
                orient='v', palette=cmap_disc)
g.set(ylim=(1,5.1))
```

[26]: [(1.0, 5.1)]



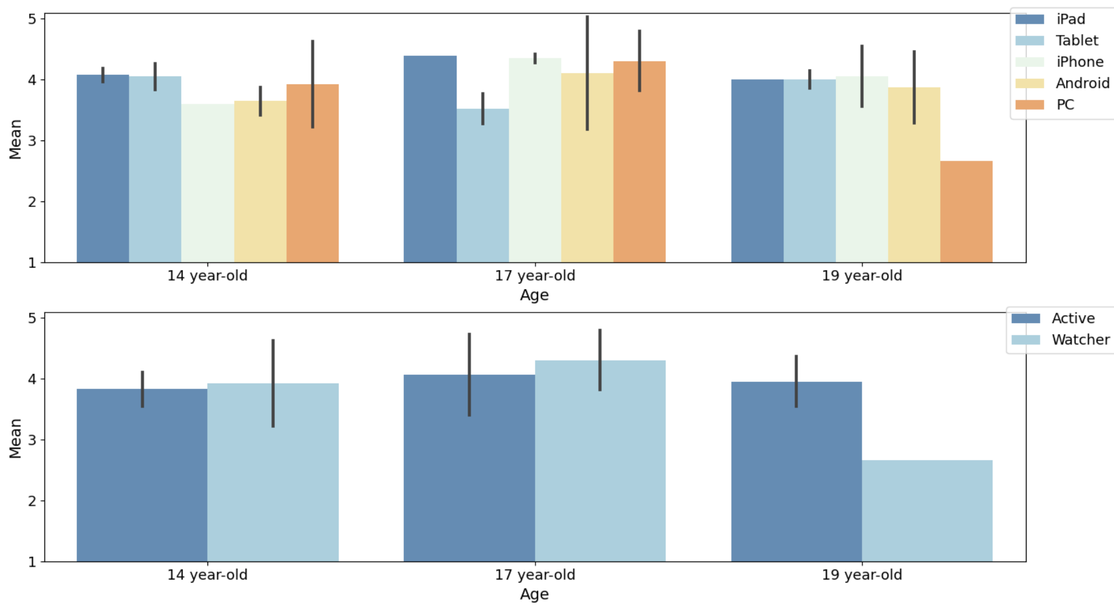
[27]:
```
g = sns.barplot(data=survey_new, y="Mean", x="Device", errorbar='sd',
                orient='v', palette=cmap_disc)
g.set(ylim=(1,5.1))
```

[27]: [(1.0, 5.1)]



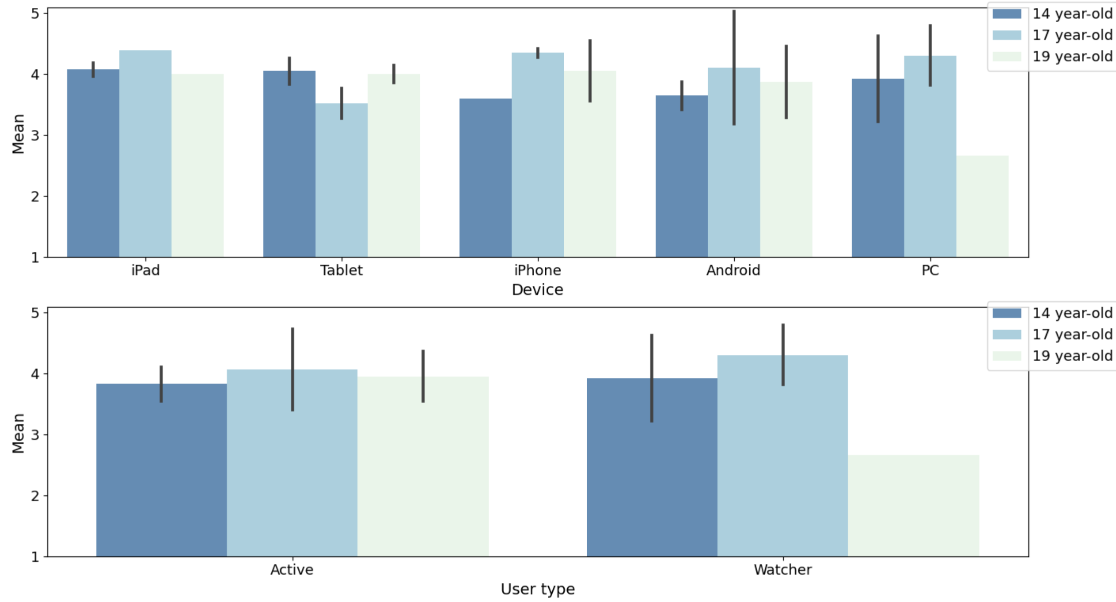
[28]:
```
fig, ax = plt.subplots(2, 1)

g = sns.barplot(data=survey_new, y="Mean", x="Age", hue="Device", errorbar='sd',
                orient='v', palette=cmap_disc, ax=ax[0])
g.set(ylim=(1,5.1))
g.legend(bbox_to_anchor=(1.1, 1.05))

g = sns.barplot(data=survey_new, y="Mean", x="Age", hue="User type",␣
 ↪errorbar='sd',
                orient='v', palette=cmap_disc, ax=ax[1])
g.set(ylim=(1,5.1))
g.legend(bbox_to_anchor=(1.1, 1.05))
```

[28]: <matplotlib.legend.Legend at 0x11b6289a0>



[29]:
```
fig, ax = plt.subplots(2, 1)

g = sns.barplot(data=survey_new, y="Mean", x="Device", hue="Age", errorbar='sd',
                orient='v', palette=cmap_disc, ax=ax[0])
g.set(ylim=(1,5.1))
g.legend(bbox_to_anchor=(1.1, 1.05))

g = sns.barplot(data=survey_new, y="Mean", x="User type", hue="Age",␣
 ↪errorbar='sd',
                orient='v', palette=cmap_disc, ax=ax[1])
g.set(ylim=(1,5.1))
g.legend(bbox_to_anchor=(1.1, 1.05))
```

[29]:
```
<matplotlib.legend.Legend at 0x11bd4e9a0>
```



1.2 xAPI statements analysis

Let's analyze now the xAPI statements collected automatically through the application. We have to combine the data from the three csv files exported from LearningLocker.

[30]:
```
salesianos_xapi = pd.read_csv('statements_salesianos_clean.csv', index_col=0).
  ↪reset_index(drop=True)
zubiri_xapi = pd.read_csv('statements_xubiri_clean.csv', index_col=0).
  ↪reset_index(drop=True)
deusto_xapi = pd.read_csv('statements_deusto_clean.csv', index_col=0).
  ↪reset_index(drop=True)
```

Let's clean the dataset before merging them. We will remove the interactions with the wrong username and rename the usernames to match the names used by students when filling the questionnaire. This way we will be able to match the results of the questionnaire with the user data from the app.

[31]:
```
# Remove Android3 as the app was not working on that device
a = ["Nuria", "Eider", "Janire", "Lucia", "unai", "Android3"]
salesianos_xapi = salesianos_xapi[~salesianos_xapi['actor'].isin(a)]
salesianos_xapi = salesianos_xapi.replace({"actor": {"Iphone 1": "iPhone1",
                                                     "iphone 1": "iPhone1",
                                                     "Ipad1": "iPad1",
                                                     "Ipad2": "iPad2"}})
salesianos_xapi["actor"] = salesianos_xapi["actor"].str.replace(" ","")
```

```
print(f'List of users for the test in Salesianos school:␣
 ↪{salesianos_xapi["actor"].unique()}')

a = ["holshola", "mario"]
zubiri_xapi = zubiri_xapi[~zubiri_xapi['actor'].isin(a)]
zubiri_xapi = zubiri_xapi.replace({"actor": {"Iphone202": "iPhone202",
                                             "IPhone202": "iPhone202",
                                             "android203": "Android203"}})
print(f'List of users for the test in Zubiri Manteo school:␣
 ↪{zubiri_xapi["actor"].unique()}')

deusto_xapi = deusto_xapi.replace({"actor": {"Iphone 101": "iPhone101",
                                  "Iphone101": "iPhone101",
                                  "AR4Education": "Android103",
                                  "pc010": "PC010",
                                  "iphone102": "iPhone102"}})
print(f'List of users for the test in Deusto school: {deusto_xapi["actor"].
 ↪unique()}')
```

```
List of users for the test in Salesianos school: ['Teacher' 'PC006' 'PC008'
'Tablet1' 'PC004' 'PC009' 'PC007' 'PC003'
 'iPhone1' 'PC005' 'iPad2' 'Tablet2' 'Android1' 'Android2' 'iPad1' 'PC002'
 'Android4']
List of users for the test in Zubiri Manteo school: ['Android201' 'Teacher'
'Android203' 'Android202' 'Android204' 'Tablet202'
 'PC028' 'iPhone201' 'iPhone202' 'Tablet201' 'iPad202' 'PC025' 'PC029'
 'PC024' 'PC023' 'PC026' 'PC022' 'PC021' 'PC011']
List of users for the test in Deusto school: ['Android102' 'Android101'
'Tablet101' 'iPad101' 'Android104' 'Tablet102'
 'Teacher' 'iPhone102' 'Android103' 'iPhone101' 'PC010']
```

[32]:
```
all_xapi = pd.concat([salesianos_xapi, zubiri_xapi, deusto_xapi], axis=0)
all_xapi.head(2)
```

[32]:
```
                          timestamp                    stored    actor
5  2023-03-10 11:45:09.638000+00:00  2023-03-10T11:45:09.638Z  Teacher  \
6  2023-03-10 11:52:00.020000+00:00  2023-03-10T11:52:00.020Z    PC006

        verb      object result
5  Logged In  Salesianos    NaN
6  Logged In  Salesianos    NaN
```

We won't count "Logged In" or "Logged Out" as interactions, since they do not contribute to the real use of the app:

[33]:
```
actions = ["Logged In", "Logged Out"]
students_app_interactions = all_xapi[~all_xapi['verb'].isin(actions)]
students_app_interactions["verb"].unique()
```

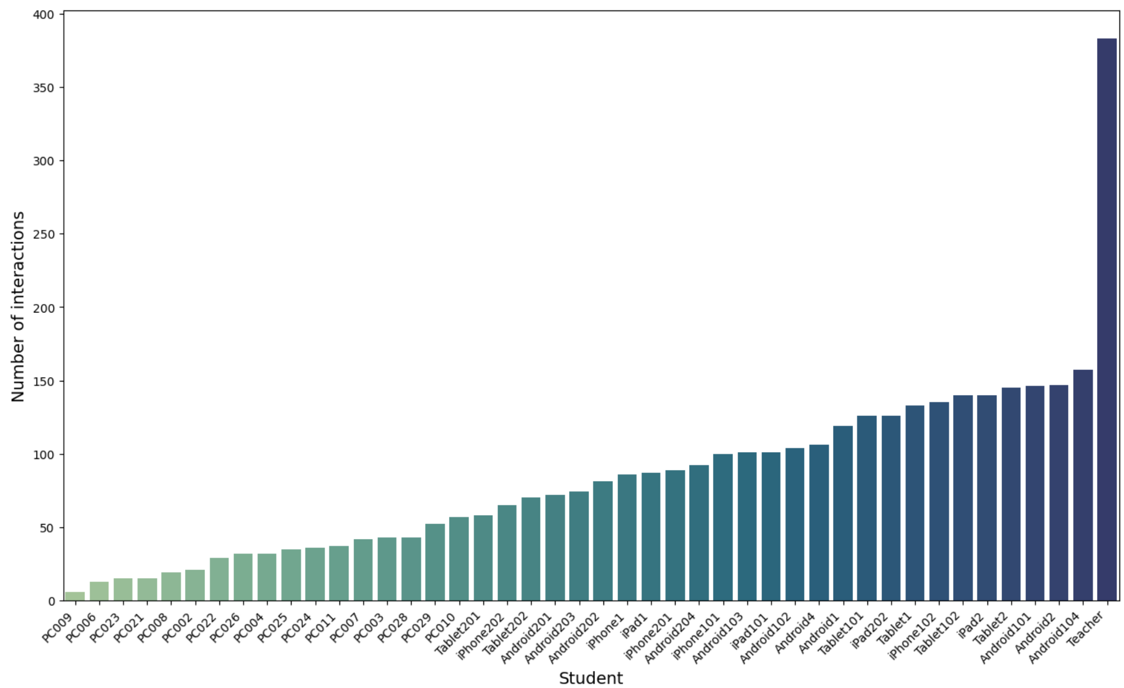
```
[33]: array(['Placed', 'Swiped', 'Asked', 'Started', 'Accepted', 'Set Turn',
             'Suggested', 'Ran Out', 'Sent', 'Checked', 'Assigned', 'Canceled',
             'Ended'], dtype=object)
```

1) Student interactions with the app (and how they correlate with the survey answers)

```
[34]: interactions = students_app_interactions.groupby(['actor'])["verb"].
       ↪agg(['count']).sort_values("count")
```

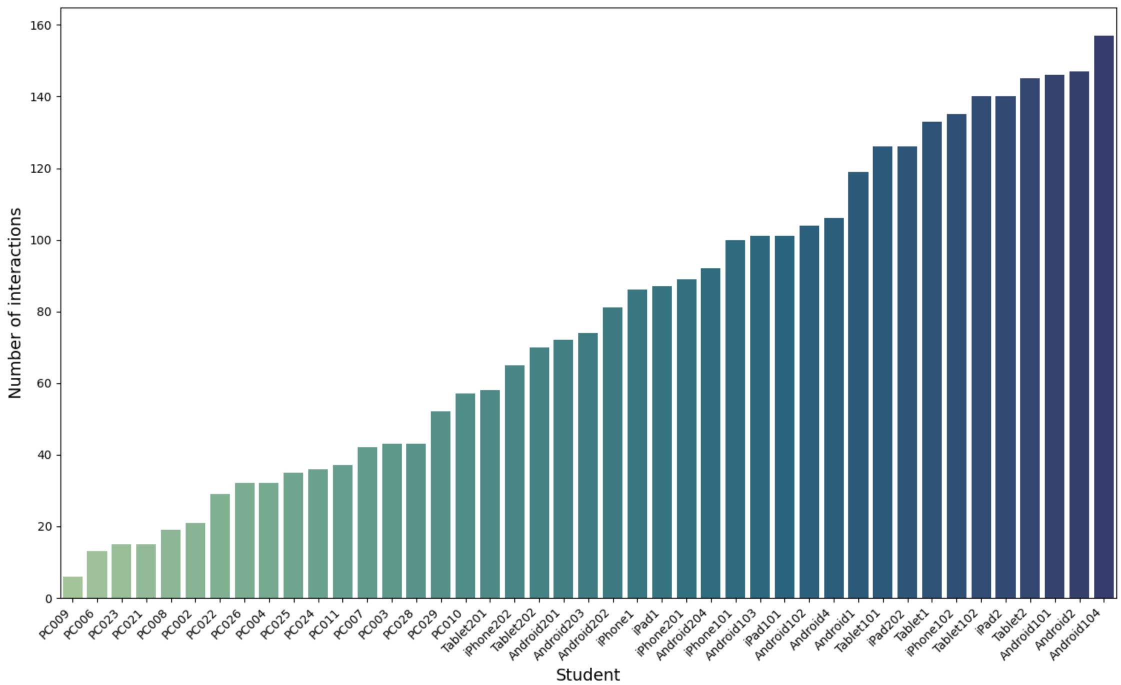
We expect that students who were in the role of *watchers*, that is the one using a PC, have significant less interactions, as they could only provide suggestions to other students, and they could not answer to the questions of the quiz or use the AR functionalities of the application.

```
[35]: sns.barplot(data=interactions, y='count', x=interactions.index, orient='v',␣
       ↪palette='crest')
      plt.ylabel("Number of interactions")
      plt.xlabel("Student")
      ax = plt.gca()
      plt.setp(ax.get_xticklabels(), rotation=45, horizontalalignment='right')
      ax.set_facecolor('white')
      plt.tick_params(labelsize=10)
```



As expected, all the *watchers* have less interactions than *active* users. The *Teacher* has by far the most interactions, but those were all generated automatically by the app, since the process of sending question, assign a score to each answer and choosing the next student were done in a automatic fashion. What's more, the *Teacher* is the only role who repeated across trials, so the count here is across the three tests. Let's remove the teacher and plot the interactions again:

[36]:
```
interactions = interactions.drop('Teacher')

sns.barplot(data=interactions, y='count', x=interactions.index, orient='v',␣
 ↪palette='crest')
plt.ylabel("Number of interactions")
plt.xlabel("Student")
ax = plt.gca()
plt.setp(ax.get_xticklabels(), rotation=45, horizontalalignment='right')
ax.set_facecolor('white')
plt.tick_params(labelsize=10)
```



The interesting aspect to analyse is whether there is any correlation between the number of interactions for each student and the answers they have given to the survey questions. We will follow two statistical approaches:

1) **Correlation analysis**: We will investigate whether there is a correlation between the number of interactions and the average scores given to the questions by the students. To do this, we will calculate the Pearson correlation coefficient and the corresponding p-value. The Pearson correlation coefficient measures the strength and direction of the linear relationship between the interactions and the scores, and the p-value indicates whether this relationship is statistically significant. If the p-value is below a significance level of 0.05, we can conclude that there is evidence of a significant correlation between the interactions and the survey scores.

2) **Hypothesis testing**: We will also perform a hypothesis test to investigate whether the survey answers given by students who had a high number of interactions are significantly different from the survey answers given by students who had a low number of interactions. We will perform a two-sample t-test assuming equal variances, which returns the t-statistic and the corresponding p-value. As in the previous analysis, if the p-value is below 0.05, we can conclude that there is evidence of a significant difference in survey answers between the two groups.

Since the interactions between the *watchers* (students on a PC) and *active* (students on a mobile device) users are significantly different, we will also perform the analysis for the PC dataset and the mobile dataset separately.

[37]:
```
interactions = interactions.reset_index()
student_list = survey_new['Mean'].reset_index()
student_list.rename(columns={"index": "Student"}, inplace=True)
```

[38]:
```
mobile_list = student_list[student_list["Student"].str.startswith(("Android",␣
↪"iPhone", "iPad", "Tablet"))]
pc_list = student_list[student_list["Student"].str.startswith(("PC"))]
```

[39]:
```
int_df = student_list.merge(interactions, left_on="Student", right_on="actor").
↪drop("actor", axis=1)
int_pc_df = pc_list.merge(interactions, left_on="Student", right_on="actor").
↪drop("actor", axis=1)
int_mobile_df = mobile_list.merge(interactions, left_on="Student",␣
↪right_on="actor").drop("actor", axis=1)
```

[40]:
```
from scipy.stats import ttest_ind, pearsonr

high_interactions = int_df["Mean"][int_df["count"] >= int_df["count"].mean()]
low_interactions = int_df["Mean"][int_df["count"] < int_df["count"].mean()]

t_stat, p_value = ttest_ind(high_interactions, low_interactions)
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}\n")

corr_coef, p_value = pearsonr(int_df["count"], int_df["Mean"])
print(f"Pearson correlation coefficient: {corr_coef}")
print(f"P-value: {p_value}")
```

```
T-statistic: -0.5063182832094194
P-value: 0.615412707444693

Pearson correlation coefficient: -0.11371060650016482
P-value: 0.47336163956268396
```

[41]:
```
high_interactions = int_mobile_df["Mean"][int_mobile_df["count"] >=␣
↪int_mobile_df["count"].mean()]
```

```
low_interactions = int_mobile_df["Mean"][int_mobile_df["count"] <␣
 ↪int_mobile_df["count"].mean()]

t_stat, p_value = ttest_ind(high_interactions, low_interactions)
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}\n")

corr_coef, p_value = pearsonr(int_mobile_df["count"], int_mobile_df["Mean"])
print(f"Pearson correlation coefficient: {corr_coef}")
print(f"P-value: {p_value}")
```

```
T-statistic: -0.29843859536657763
P-value: 0.7679370544701799

Pearson correlation coefficient: -0.060131363781654665
P-value: 0.7704429581178198
```

[42]:
```
high_interactions = int_pc_df["Mean"][int_pc_df["count"] >= int_pc_df["count"].
 ↪mean()]
low_interactions = int_pc_df["Mean"][int_pc_df["count"] < int_pc_df["count"].
 ↪mean()]

t_stat, p_value = ttest_ind(high_interactions, low_interactions)
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}\n")

corr_coef, p_value = pearsonr(int_pc_df["count"], int_pc_df["Mean"])
print(f"Pearson correlation coefficient: {corr_coef}")
print(f"P-value: {p_value}")
```

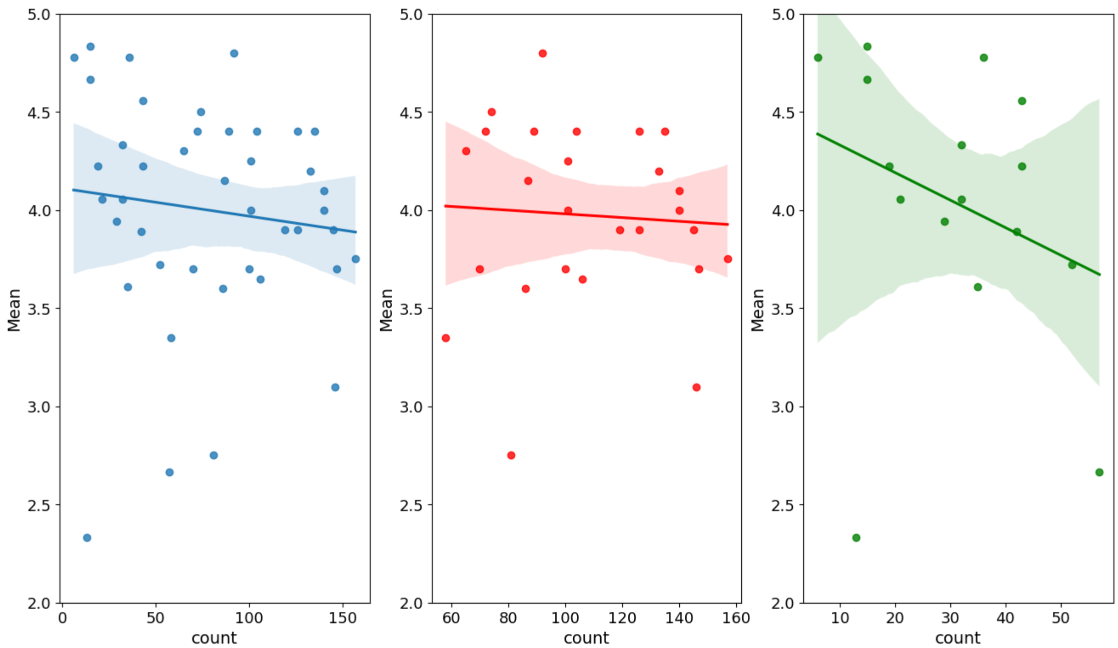
```
T-statistic: -0.3712121842436294
P-value: 0.7160367243263036

Pearson correlation coefficient: -0.29050233285635907
P-value: 0.27505038362052325
```

Since none of the p-values are below the significance level of 0.05 we have set and the correlation coefficients are very close to 0, we can conclude that there is no significant relationship between the number of interactions and the average survey answers of the students. Let's show the linear relationship on a scatterplot

[43]:
```
f, axes = plt.subplots(1, 3)

sns.regplot(x="count", y="Mean", data=int_df, ax=axes[0]);
sns.regplot(x="count", y="Mean", data=int_mobile_df, ax=axes[1], color='red',␣
 ↪line_kws={'color': 'red'});
sns.regplot(x="count", y="Mean", data=int_pc_df, ax=axes[2], color='green',␣
 ↪line_kws={'color': 'green'});
```

```
#axes[0].set_xlim([10, 120])
axes[0].set_ylim([2, 5])
#axes[1].set_xlim([50, 120])
axes[1].set_ylim([2, 5])
#axes[2].set_xlim([10, 60])
axes[2].set_ylim([2, 5])
```

[43]: (2.0, 5.0)



2) Active users - Students' grades When the *active users* (students using a mobile device and receiving questions from the app) submit an answer, the app assigns them a grade, which can be found in the "Assigned" action. We will study whether there is correlation between the grade the students have obtained and their answers to the survey.

[44]:
```
df = all_xapi[(all_xapi["actor"]=="Teacher") & (all_xapi["verb"]=="Assigned")]
df.head()
```

[44]:
```
                            timestamp                    stored    actor
321  2023-03-10 12:04:36.832000+00:00  2023-03-10T12:04:36.832Z  Teacher  \
373  2023-03-10 12:05:37.368000+00:00  2023-03-10T12:05:37.368Z  Teacher
402  2023-03-10 12:06:24.752000+00:00  2023-03-10T12:06:24.752Z  Teacher
546  2023-03-10 12:11:20.420000+00:00  2023-03-10T12:11:20.420Z  Teacher
587  2023-03-10 12:12:12.001000+00:00  2023-03-10T12:12:12.001Z  Teacher

         verb         object result
321  Assigned  7.72;iPhone_1    NaN
```

```
373  Assigned  8.15;Android2    NaN
402  Assigned   7.72;Tablet1    NaN
546  Assigned  7.45;Tablet_2    NaN
587  Assigned     7.72;iPad2    NaN
```

In the above dataframe we can see where the grades are stored. We need to extract them and clean the user names.

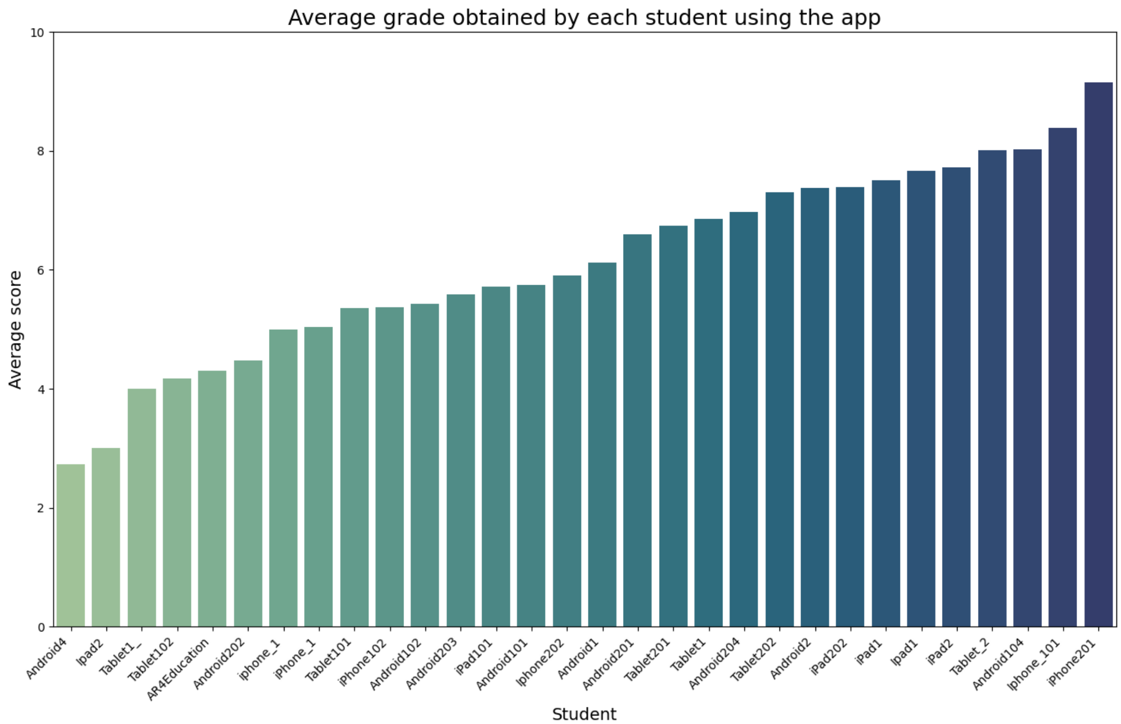
[45]:
```
grades = pd.DataFrame(df["object"].str.split(";", expand=True))
grades.columns = ["Score", "Student"]
grades.head()
```

[45]:

	Score	Student
321	7.72	iPhone_1
373	8.15	Android2
402	7.72	Tablet1
546	7.45	Tablet_2
587	7.72	iPad2

[46]:
```
grades["Score"] = grades["Score"].astype("float")
grades = grades.groupby('Student', as_index=False)['Score'].mean().
 ↪sort_values("Score")
```

[47]:
```
sns.barplot(data=grades, y='Score', x='Student', orient='v', palette='crest')
plt.title('Average grade obtained by each student using the app')
plt.ylabel("Average score")
plt.xlabel("Student")
ax = plt.gca()
plt.setp(ax.get_xticklabels(), rotation=45, horizontalalignment='right')
ax.set_facecolor('white')
plt.ylim(0, 10)
plt.tick_params(labelsize=10)
```



We will now perform the same analysis as in the previous section with the survey answers to see if there is correlation between the survey answers and the grades obtained.

[48]:
```
grade_df = student_list.merge(grades, left_on="Student", right_on="Student")
grade_df.head(3)
```

[48]:

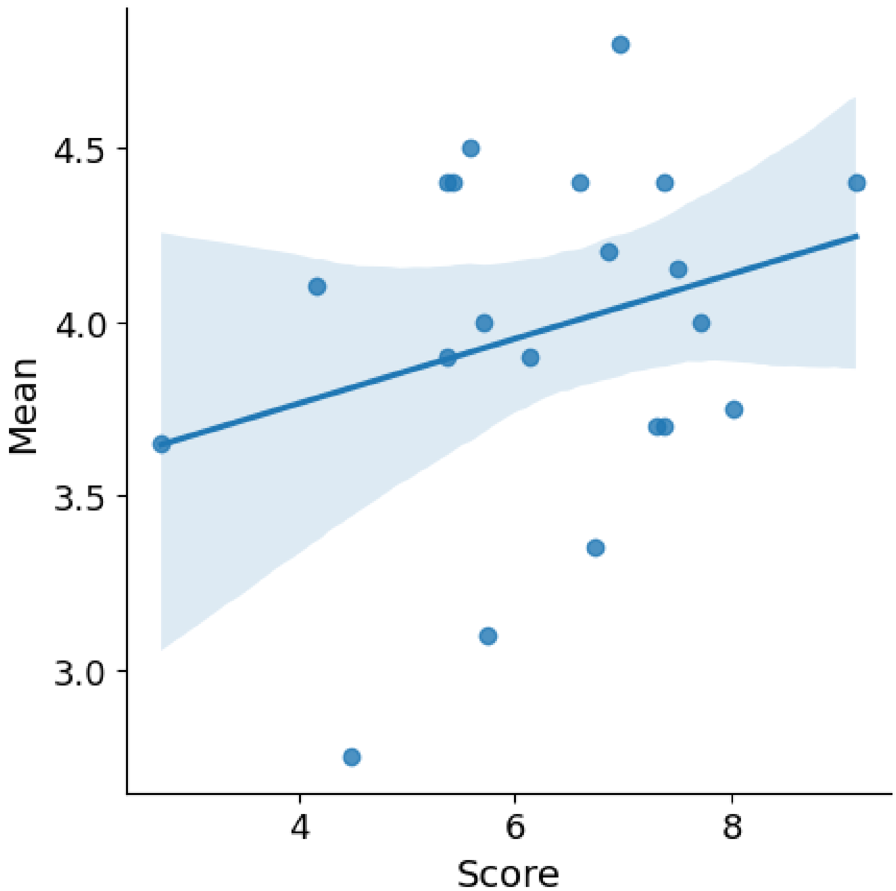
	Student	Mean	Score
0	iPad1	4.15	7.50
1	iPad2	4.00	7.72
2	Tablet1	4.20	6.86

[49]:
```
high_grade = grade_df["Mean"][grade_df["Score"] >= grade_df["Score"].mean()]
low_grade = grade_df["Mean"][grade_df["Score"] < grade_df["Score"].mean()]

t_stat, p_value = ttest_ind(high_grade, low_grade)
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}\n")

corr_coef, p_value = pearsonr(grade_df["Score"], grade_df["Mean"])
print(f"Pearson correlation coefficient: {corr_coef}")
print(f"P-value: {p_value}")
```

```
T-statistic: 0.953006398730349
P-value: 0.3525546309185852
```

```
Pearson correlation coefficient: 0.27553882521336226
P-value: 0.22668801730770263
```

[50]:
```
sns.lmplot(x="Score", y="Mean", data=grade_df);
```



There seem to be a correlation between the variables, but without a p-value below the significance threshold. Another interesting focus point would be to study the correlation between the number of interactions by the mobile-only students and the grades they've obtained:

[51]:
```
int_grade_df = interactions.merge(grades, left_on="actor", right_on="Student").
  ↪drop("Student", axis=1)
int_grade_df.head(3)
```

[51]:

	actor	count	Score
0	Tablet201	58	6.735
1	Tablet202	70	7.300
2	Android201	72	6.600

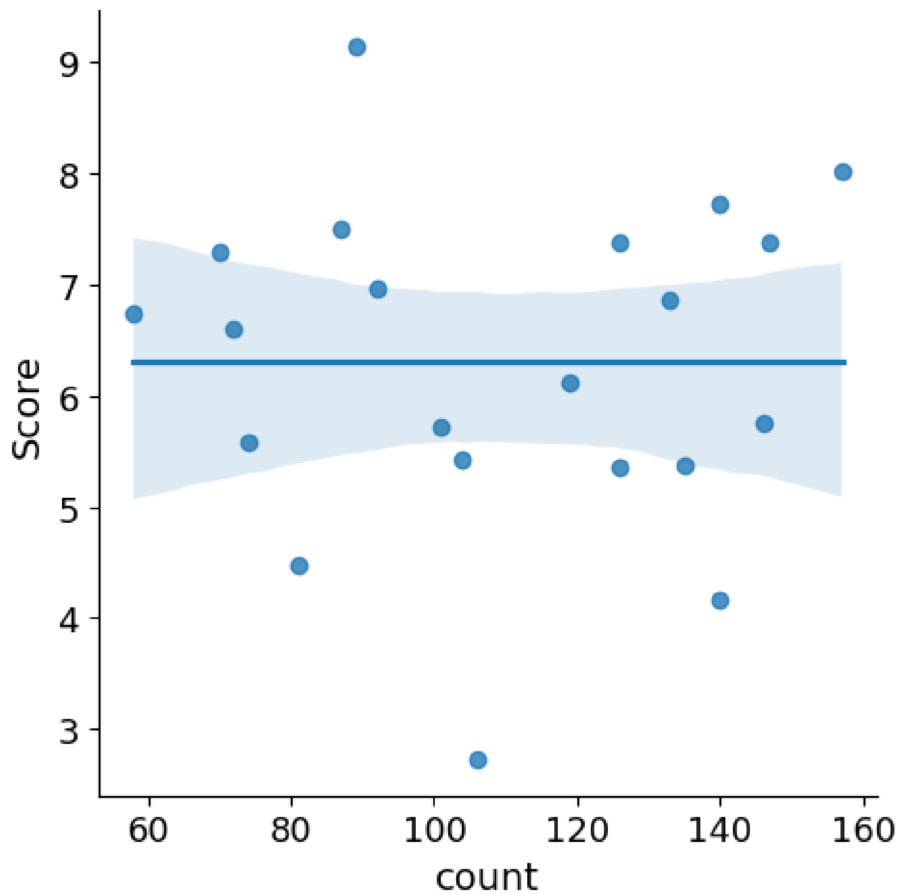
[52]:

```
high_grade = int_grade_df["count"][int_grade_df["Score"] >=␣
 ↪int_grade_df["Score"].mean()]
low_grade = int_grade_df["count"][int_grade_df["Score"] < int_grade_df["Score"].
 ↪mean()]

t_stat, p_value = ttest_ind(high_grade, low_grade)
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}\n")

corr_coef, p_value = pearsonr(int_grade_df["Score"], int_grade_df["count"])
print(f"Pearson correlation coefficient: {corr_coef}")
print(f"P-value: {p_value}")
```

```
T-statistic: -0.5088044707659332
P-value: 0.6167468678465822

Pearson correlation coefficient: 2.4102820336269204e-05
P-value: 0.9999172681085955
```

[53]:

```
sns.lmplot(x="count", y="Score", data=int_grade_df);
```



And in this case, again we cannot find any meaningful correlations in the data.

3) Accepted suggestions Let's have a look if the suggestions sent by the users were accepted from the students when answering the questions:

[54]:
```
accepted_suggestions = students_app_interactions[students_app_interactions["verb"]=="Accepted"]
```

[55]:
```
accepted = accepted_suggestions.groupby(['actor'])["verb"].agg(['count']).sort_values("count").reset_index()
accepted.head()
```

[55]:

	actor	count
0	Android1	2
1	iPhone101	3
2	iPhone1	3
3	iPad202	3
4	iPad1	3

We will perform the same analysis as before, first with the survey answers:

[56]:
```
accepted_df = student_list.merge(accepted, left_on="Student", right_on="actor").drop("actor", axis=1)
accepted_df
```

[56]:

	Student	Mean	count
0	iPad1	4.15	3
1	iPad2	4.00	4
2	Tablet1	4.20	4
3	Tablet2	3.90	4
4	iPhone1	3.60	3
5	Android1	3.90	2
6	Android2	3.70	4
7	Android4	3.65	4
8	iPad202	4.40	3
9	Tablet201	3.35	3
10	Tablet202	3.70	3
11	iPhone201	4.40	3
12	iPhone202	4.30	3
13	Android201	4.40	3
14	Android202	2.75	3
15	Android203	4.50	3
16	Android204	4.80	4
17	iPad101	4.00	4
18	Tablet101	3.90	4
19	Tablet102	4.10	4

```
20   iPhone101  3.70      3
21   iPhone102  4.40      4
22  Android101  3.10      5
23  Android102  4.40      5
24  Android103  4.25      4
25  Android104  3.75      4
```

[57]:
```python
high_accepted = accepted_df["count"][accepted_df["Mean"] >= accepted_df["Mean"].
 ↪mean()]
low_accepted = accepted_df["count"][accepted_df["Mean"] < accepted_df["Mean"].
 ↪mean()]

t_stat, p_value = ttest_ind(high_accepted, low_accepted)
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}\n")

corr_coef, p_value = pearsonr(accepted_df["Mean"], accepted_df["count"])
print(f"Pearson correlation coefficient: {corr_coef}")
print(f"P-value: {p_value}")
```

```
T-statistic: 0.509027810380622
P-value: 0.6153809157159337

Pearson correlation coefficient: 0.018954251113930235
P-value: 0.9267752560896472
```

This test shows us that there is no clear correlation in this case. Let's check with the grades:

[58]:
```python
accepted_grades_df = grades.merge(accepted, left_on="Student",␣
 ↪right_on="actor").drop("actor", axis=1)
accepted_grades_df.head()
```

[58]:

	Student	Score	count
0	Android4	2.726667	4
1	Tablet102	4.166667	4
2	Android202	4.476667	3
3	Tablet101	5.362500	4
4	iPhone102	5.366667	4

[59]:
```python
high_accepted = accepted_df["count"][accepted_df["Mean"] >= accepted_df["Mean"].
 ↪mean()]
low_accepted = accepted_df["count"][accepted_df["Mean"] < accepted_df["Mean"].
 ↪mean()]

t_stat, p_value = ttest_ind(high_accepted, low_accepted)
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}\n")
```

```
corr_coef, p_value = pearsonr(accepted_df["Mean"], accepted_df["count"])
print(f"Pearson correlation coefficient: {corr_coef}")
print(f"P-value: {p_value}")
```

```
T-statistic: 0.509027810380622
P-value: 0.6153809157159337

Pearson correlation coefficient: 0.018954251113930235
P-value: 0.9267752560896472
```

There is no correlation in this case either.

1.2.1 4) Time left in students' answer.

Our final step in the analysis will focus on the time left for the students. Each student had 40 seconds to answer a question, after he accepted the request from the app. We will analyse its correlation with the grades.

[60]:
```
time_left = students_app_interactions[students_app_interactions["verb"]=="Sent"]
time_left.head()
```

[60]:
```
                          timestamp                    stored     actor  
319  2023-03-10 12:04:36.804000+00:00  2023-03-10T12:04:36.804Z   iPhone1   \
372  2023-03-10 12:05:37.358000+00:00  2023-03-10T12:05:37.358Z  Android2
401  2023-03-10 12:06:24.739000+00:00  2023-03-10T12:06:24.739Z   Tablet1
545  2023-03-10 12:11:20.415000+00:00  2023-03-10T12:11:20.415Z   Tablet2
589  2023-03-10 12:12:12.009000+00:00  2023-03-10T12:12:12.009Z     iPad2

     verb
319  Sent  \
372  Sent
401  Sent
545  Sent
589  Sent

object
319  (0.3478570580482483,_0.34704893827438354, 0.09247999638319016), (39.94,
14.89) 19  \
372   (0.3337985873222351,_0.3722161054611206, 0.005822139326483011), (44.10,
1.00) 14
401  (0.30835631489753723,_0.39220741391181946, 0.033011842519044876), (46.51,
6.11) 5
545    (0.2722242474555969,_0.4184000790119171, 0.02890080213546753), (51.65,
6.06) 27
589     (0.3397345244884491,_0.3627608120441437, 0.05463578924536705), (42.50,
9.14) 4

    result
```

```
319    NaN
372    NaN
401    NaN
545    NaN
589    NaN
```

[61]:
```python
time_df = pd.DataFrame(all_xapi[all_xapi["verb"]=="Sent"]["object"].str.
 ↪split("\) ", expand=True))
time_df.columns = ["student", "time"]
time_df = time_df[["time"]]
time_left["Time"] = time_df
time_left.head()
```

```
/var/folders/mb/gp2pv4vs4tb05cb9df4whm7r0000gn/T/ipykernel_11150/1717799992.py:4
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  time_left["Time"] = time_df
```

[61]:
```
                           timestamp                    stored     actor
319  2023-03-10 12:04:36.804000+00:00  2023-03-10T12:04:36.804Z   iPhone1  \
372  2023-03-10 12:05:37.358000+00:00  2023-03-10T12:05:37.358Z  Android2
401  2023-03-10 12:06:24.739000+00:00  2023-03-10T12:06:24.739Z   Tablet1
545  2023-03-10 12:11:20.415000+00:00  2023-03-10T12:11:20.415Z   Tablet2
589  2023-03-10 12:12:12.009000+00:00  2023-03-10T12:12:12.009Z     iPad2

     verb
319  Sent  \
372  Sent
401  Sent
545  Sent
589  Sent

object
319  (0.3478570580482483,_0.34704893827438354, 0.09247999638319016), (39.94,
14.89) 19  \
372   (0.3337985873222351,_0.3722161054611206, 0.005822139326483011), (44.10,
1.00) 14
401  (0.30835631489753723,_0.39220741391181946, 0.033011842519044876), (46.51,
6.11) 5
545    (0.2722242474555969,_0.4184000790119171, 0.02890080213546753), (51.65,
6.06) 27
589     (0.3397345244884491,_0.3627608120441437, 0.05463578924536705), (42.50,
9.14) 4
```

```
     result  Time
319     NaN    19
372     NaN    14
401     NaN     5
545     NaN    27
589     NaN     4
```

[62]:
```
time_left_df = time_left[["actor", "Time"]]
```

[63]:
```
time_left_df["Time"] = time_left_df["Time"].astype("float")
time_left_df = time_left_df.groupby('actor', as_index=False)['Time'].mean().
 ↪sort_values("Time")
```

```
/var/folders/mb/gp2pv4vs4tb05cb9df4whm7r0000gn/T/ipykernel_11150/4087081215.py:1
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  time_left_df["Time"] = time_left_df["Time"].astype("float")
```

[64]:
```
time_grades_df = grades.merge(time_left_df, left_on="Student",␣
 ↪right_on="actor").drop("actor", axis=1)
time_grades_df.head()
```

[64]:

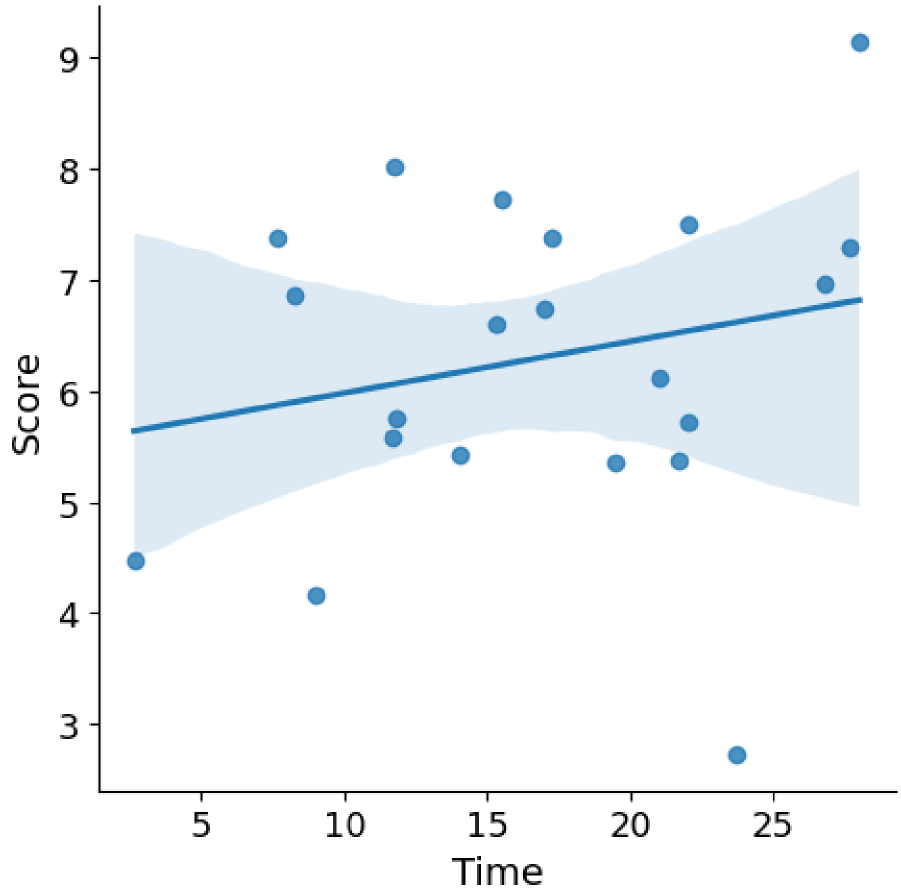
	Student	Score	Time
0	Android4	2.726667	23.666667
1	Tablet102	4.166667	9.000000
2	Android202	4.476667	2.666667
3	Tablet101	5.362500	19.500000
4	iPhone102	5.366667	21.666667

[65]:
```
high = time_grades_df["Time"][time_grades_df["Score"] >=␣
 ↪time_grades_df["Score"].mean()]
low = time_grades_df["Time"][time_grades_df["Score"] < time_grades_df["Score"].
 ↪mean()]

t_stat, p_value = ttest_ind(high, low)
print(f"T-statistic: {t_stat}")
print(f"P-value: {p_value}\n")

corr_coef, p_value = pearsonr(time_grades_df["Score"], time_grades_df["Time"])
print(f"Pearson correlation coefficient: {corr_coef}")
print(f"P-value: {p_value}")
```

```
T-statistic: 0.7127243955666976
P-value: 0.4846781489242483
```

```
Pearson correlation coefficient: 0.22349958103438405
P-value: 0.33011481978668883
```

[66]:
```python
sns.lmplot(x="Time", y="Score", data=time_grades_df);
```



There is no correlation in this case either.

1.3 Machine learning based analysis: dimensionality reduction and clustering of the data

Even though the reduced number of data points (44 total students) for this use case makes the application of machine learning a difficult task, we can still try something. For instance, let's focus only on the mobile students, since they have a greater number of features to work with. Let's assume that the average grade they obtain in the app (which we have analysed above) is a function of the number of interactions they have made, the number of accepted suggestions, the time they have left, and the average score for the survey answers.

We will apply a PCA (Principal Component Analysis) model to find out the principal components that explain the variance in the data, in this case the obtained grades. We will also be able to visualize the relationships between the principal components and the grades in a 2D space and create clusters for them.

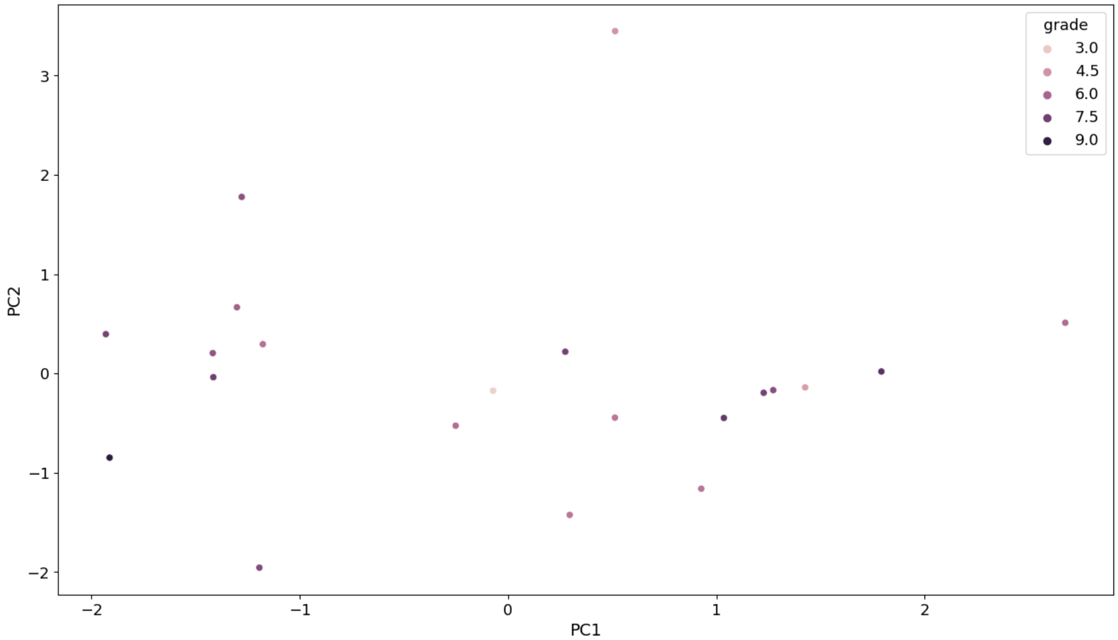
[67]:
```
accepted_suggestions = accepted_grades_df.drop("Score", axis=1)
```

[68]:
```
df_ai = time_grades_df.merge(accepted_suggestions, left_on="Student",␣
 ↪right_on="Student")
ai = df_ai.merge(int_mobile_df, left_on="Student", right_on="Student")
ai.columns = ["student", "grade", "time_left", "accepted_suggestions",␣
 ↪"survey_score", "interactions"]
ai.head()
```

[68]:
```
      student     grade  time_left  accepted_suggestions  survey_score  \
0    Android4  2.726667  23.666667                     4          3.65
1   Tablet102  4.166667   9.000000                     4          4.10
2  Android202  4.476667   2.666667                     3          2.75
3   Tablet101  5.362500  19.500000                     4          3.90
4   iPhone102  5.366667  21.666667                     4          4.40

   interactions
0           106
1           140
2            81
3           126
4           135
```

[69]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans

X = ai.drop(["grade", "student"], axis=1)

scaler = StandardScaler()
X_std = scaler.fit_transform(X)

pca = PCA(n_components=2)
principal_components = pca.fit_transform(X_std)

result = pd.DataFrame(principal_components, columns=['PC1', 'PC2'])
result['grade'] = ai['grade']

sns.scatterplot(x='PC1', y='PC2', hue='grade', data=result)
```

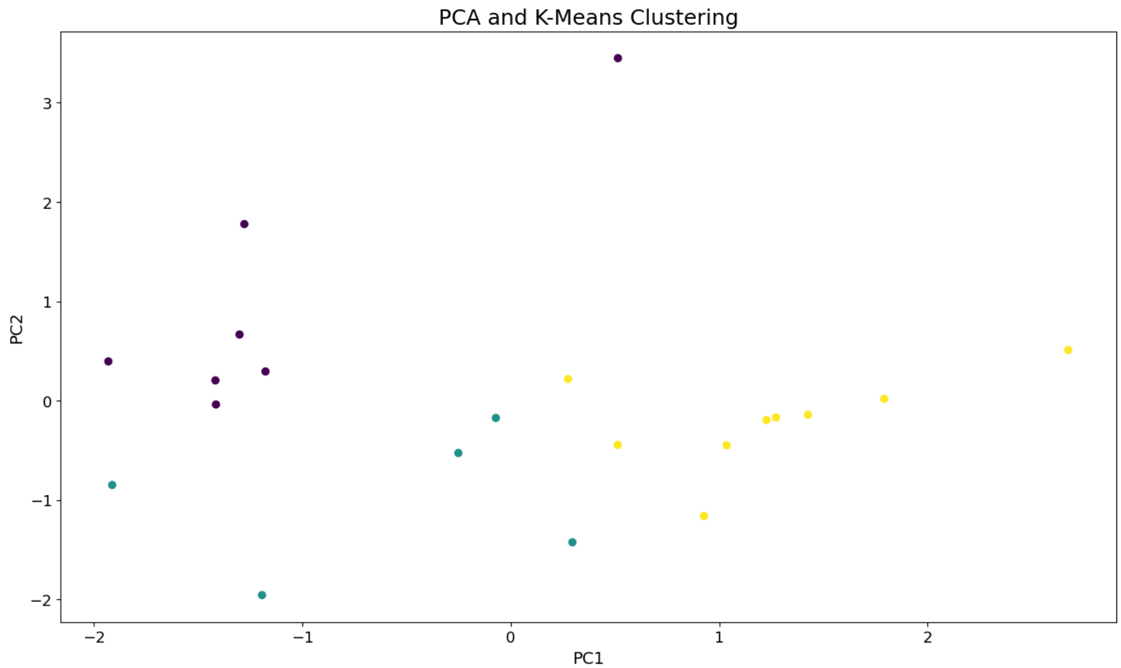
[69]:
```
<Axes: xlabel='PC1', ylabel='PC2'>
```



We have applied the PCA model and now we can identify clusters using KMeans:

[70]:
```
kmeans = KMeans(n_clusters=3, n_init='auto')
kmeans.fit(principal_components)
cluster_labels = kmeans.labels_
```

[71]:
```
plt.scatter(principal_components[:, 0], principal_components[:, 1],␣
  ↪c=cluster_labels)
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.title('PCA and K-Means Clustering')
plt.show()
```

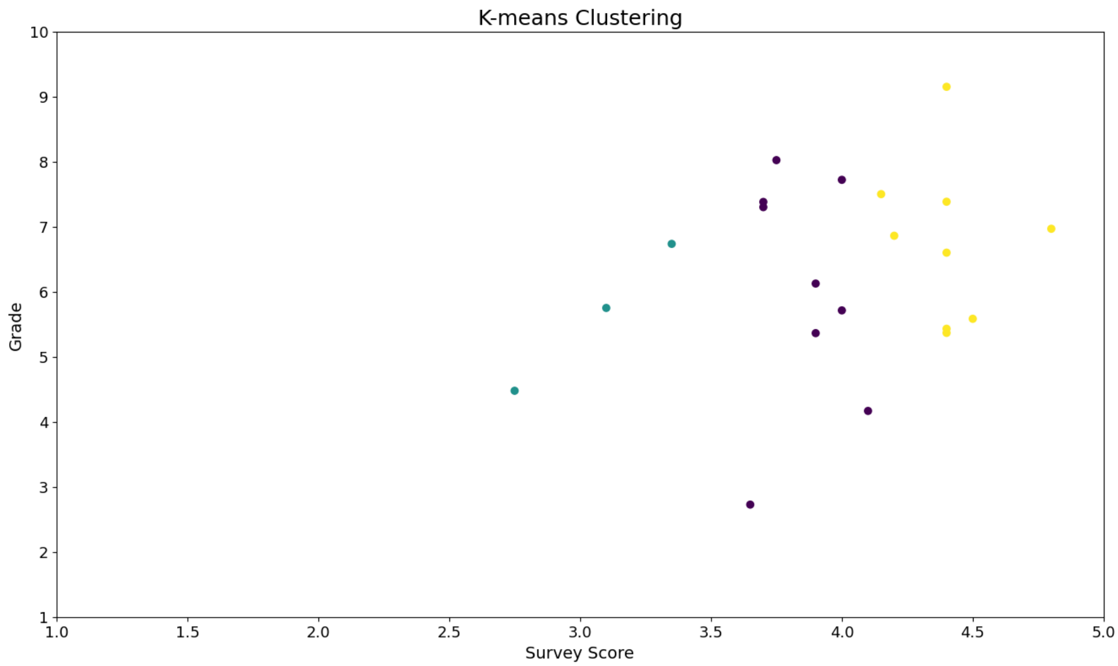


The three clusters appear to be quite scattered

[72]:
```
## TODO
# Study number of possible clusters
# KMeans prior to PCA
# What variables explain the PCA
# Other clustering algo?
```

We can also try creating clusters for the survey scores:

[73]:
```
X = ai["survey_score"].values.reshape(-1, 1)
X_std = (X - X.mean(axis=0)) / X.std(axis=0)

kmeans = KMeans(n_clusters=3, n_init='auto')

kmeans.fit(X_std)

cluster_labels = kmeans.labels_

plt.scatter(X[:, 0], ai['grade'], c=cluster_labels)
plt.xlabel('Survey Score')
plt.xlim(1, 5)
plt.ylim(1, 10)
plt.ylabel('Grade')
plt.title('K-means Clustering')
plt.show()
```



1.4 Conclusions:

TODO