Can data analytics and AI reshape and optimize learning in education?

Over the years, students in traditional classrooms often receive a one-size-fits-all approach to learning, which doesn't account for individual learning styles, abilities, or needs. This can lead to disengagement, poor academic performance, and gaps in understanding. For example, some students grasp concepts quickly, while others may need more time. Other students may prefer visual, auditory, or kinesthetic learning methods, but traditional methods often focus on one or two, so there are different learning styles. On the other hand, teachers could also have some trouble providing real- time feedback, so they may not be able to provide immediate insights or adjustments based on individual student performance. Also, it might be difficult for educators to consistently gauge how engaged or disengaged each student is with the learning material. Therefore, it is well known that the operation of a course cannot be a hundred percent efficient, neither from the side of the students nor from the teachers. This is why artificial intelligence and data analytics have come to identify these problems, and to find ways to solve them.

Through teaching in a classroom, we see that some students are better than others and this is reflected in their grades, the result of learning. There is not just one cause why some students struggle while others succeed. Since in a class the people who define it are usually of the same age, this biological factor will also determine the groups into which the data tables we have will be divided. Depending on the age, corresponding data are added, such as whether the student works in parallel, or whether has help from home for studying the courses, and much more. The data that we can get and produce can be the gender, the hours of study outside of school, the hours they spent on social media platforms, their stress level, their financial situation (their own or their family's), how much help they have from parents or tutoring, etc. As we can see, there are many factors that influence the performance level of learning, so we can conclude that if some students have the same score of a factor, for example they don't do an any extracurricular activities, they won't necessarily have the same grade outcome. Data analysis is here to help our minds with the collection of many data factors to create a pattern for a better educational level. Can AI tools optimize learning processes and enhance educational content delivery? How can analytics identify learning patterns and improve personalized learning?

For this research project, we are going to use Kaggle datasets related to education and its learning factors. Since we used a lot of datasets, we saw that the constant factors are like each other from dataset to dataset. The 'Key Attributes', as it is said in the first dataset we read are divided into categories. For example, the first category is about demographics, which concludes school, sex, age, address type, family size, parent's cohabitation status. It is also referred to paternal background, such as their education level, occupation. Another category is about the academic support, more specifically the extra educational support, paid classes, family support. The student activities have an important role for a child's learning: extracurricular activities, internet access, romantic relationship status. Also, the personal and social life of a student, such as study time, travel time, family relationships, free time, alcohol consumption. Finally, the academic performance shows the outcome of the effort made, indicated as grades across three periods (G1, G2, G3), number of school absences, and past class failures.

The tools used to complete this paperwork were SQL, Spyder Anaconda, Excel, Kaggle. This paper started to be written on 15/10/2024.

Contents

Affecting Students’ Performance Factors

The identification of factors affecting the academic performance of students has always been one of the most important tasks of researchers and educational psychologists, as well as one of the challenges faced by medical universities. To this end, researchers have focused on recognizing the role of motivation, learning strategies, and academic emotions in learning and student achievement.

Motivation is a multifaceted concept that is considered in several disciplines as it is defined as the driving force behind human actions and is not obvious from the outside. Placing the focus on the cognitive approach, motivation is defined as the process that stimulates and supports purposeful activity. Motivational factors such as interest, autonomy, competence, family and self-efficacy determine the regulatory efforts of students to achieve the learning goal. In a selfregulated learning environment, such as higher education or online learning, motivation is critical to successful learning. It is believed that self-regulating learning processes are interrelated to motivational processes as motivation affects the choice of learning strategy, learning processes, and outcomes. Similarly, self-regulation can influence student motivation. Academic self-esteem describes the cognitive representation of the perceived abilities of a person in the context of academic achievement. As for learning outcomes, it is important that intrinsic motivation relates to learners’ perceived competence and can be supported by skill selection, as well as challenging tasks and feedback postulating a causal influence of the academic selfconcept on intrinsic motivation. Academic self-efficacy refers to students’ beliefs and attitudes towards their ability to achieve academic success, as well as the belief in their ability to accomplish academic tasks and study the material successfully. Students with high self-efficacy associate their failure with fewer attempts rather than lower ability, while students with low selfefficacy attribute their failures to their poor abilities. The studies involving 214 psychology students from Saudi Arabian universities have shown that academic self-efficacy has a positive and significant effect on their academic performance. In addition, academic self-efficacy has a significant impact on student learning, motivation, and academic performance as evidenced by a number of scientific studies. The ARCS (Attention, Relevance, Confidence, Satisfaction) model aims to integrate and thus illustrate the relationship between the theoretical concepts of will, motivation, learning, and performance to facilitate research and instructional design to create a motivating (online) learning environment. The model includes four components are the attention related to the level of curiosity, the relevance of the learning objective to the learner, including its perceived value, the confidence in the success of the learning activity, including the attribution of the learning outcome, and satisfaction with the assessed quality of the learning outcome and the learning process [1]. These four components are complemented by will, which includes self-regulation strategies to maintain purposeful behavior. Psychologically, motivation to learn is described as the student’s energy and aspiration to learn, work efficiently, and fulfill their potential along with the behavior associated with those intentions. It should be highlighted that the curriculum of higher education used to be based primarily on cognitive approaches rather than the theory of motivation; therefore, motivation to learn is still underestimated. The Association for Medical Education in Europe guidance on Motivation in Medical Education notes that medical students should be motivated in connection to the fact that they receive highly specialized education. Motivation is a major determinant of the quality and success of learning, the lack of which may well explain why there are disaffected, discouraged, or dropping out medical students. Therefore, it is very important to know what drives students to learn, as well as the methods that can guide teachers to help them choose teaching approaches and ultimately influence student outcomes, including their retention in the institution.

Personalized Learning Strategy using Data analytics, as a Tool to Improve Academic Performance and Motivation of Students

Data analytics plays a critical role in personalized education by providing educators with valuable insights and tools to tailor instruction and support to individual students. By leveraging the power of data analytics, educational institutions can create dynamic and engaging learning environments that meet the unique needs of each learner.

Personalized education is a student-centered approach that recognizes and responds to the individual needs, interests, and learning styles of each student. In this section, we will delve into the origin and evolution of personalized education, explore its benefits, and discuss the challenges involved in implementing this approach.

With data analytics, educators can move beyond traditional assessments and gain a more comprehensive understanding of student learning. It helps identify trends, patterns, and correlations that may not be immediately apparent, allowing educators to make data-informed adjustments to curriculum, instructional strategies, and support systems [2]. In the realm of education, various types of data are collected to gain insights into student performance and learning processes. These include the **Assessment Data**, which includes standardized test scores, quizzes, exams, and other formal assessments that measure student knowledge and skills. **Attendance and Engagement Data** are data on student attendance, participation in class, engagement with learning materials, and interactions with peers and teachers provide insights into student motivation and involvement in the learning process. **Behavioral Data** includes information on student behavior, discipline records, and social-emotional indicators, which help understand factors that may impact student learning and well-being. **Learning Management System (LMS) Data** collect data on student interactions with digital learning materials, such as time spent on tasks, completion rates, and progress through modules. This data provides insights into student engagement and learning progression. **Socioeconomic and Demographic Data** concludes Information about students' socioeconomic background, language proficiency, and demographic factors can help identify disparities and tailor interventions to meet specific needs.

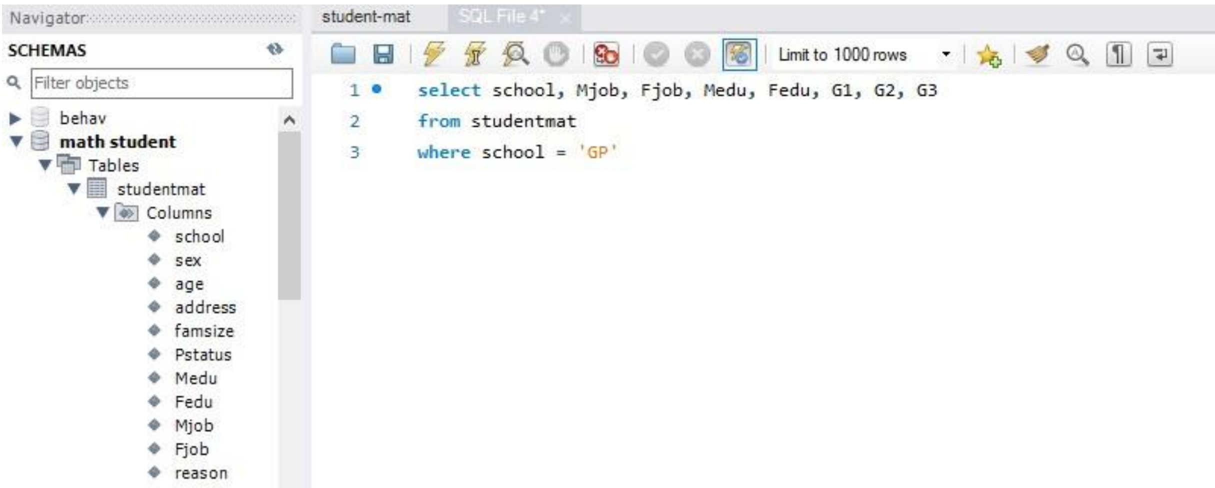
Using these data, it is easy to proceed with predictive analytics, which is a subfield of data analytics, utilizes historical data to make predictions about future outcomes. In education, predictive analytics can be used to anticipate student performance, identify at-risk students, and provide early interventions to prevent academic difficulties.

By analyzing historical data patterns, predictive analytics algorithms can identify factors that contribute to student success or failure. These factors may include attendance, engagement, past academic performance, socio-economic background, and more. Predictive analytics models can then generate actionable insights, alerting educators to students who may require additional support or intervention [2]. Predictive analytics also assists in identifying trends and patterns at the institutional level. It enables educational institutions to anticipate enrollment patterns, optimize resource allocation, and identify areas where targeted interventions or improvements may be necessary.

So, depending on the previous facts about these factors that influence student performance and learning, we will start collecting data and clear those in order to come to an outcome.

The impact of Parental Education and Occupation on Student Performance

The first thing we are going to examine about this dataset (Student Performance in Mathematics and Portuguese) [3], is to analyze the impact of parental education and occupation on student performance. With SQL Workbench, we cleared some data, using the select clause to isolate the data we want (Pic1, Pic2).



Pic1: SQL code selecting one school and the data we want to examine

school	Mjob	Fjob	Medu	Fedu	G1	G2	G3
GP	at_home	teacher	4	4	5	6	6
GP	at_home	other	1	1	5	5	6
GP	at_home	other	1	1	7	8	10
GP	health	services	4	2	15	14	15
GP	other	other	3	3	6	10	10
GP	services	other	4	3	15	15	15
GP	other	other	2	2	12	12	11
GP	other	teacher	4	4	6	5	6
GP	services	other	3	2	16	18	19
GP	other	other	3	4	14	15	15
GP	teacher	health	4	4	10	8	9
GP	services	other	2	1	10	12	12
GP	health	services	4	4	14	14	14
GP	teacher	other	4	3	10	10	11
GP	other	other	2	2	14	16	16
GP	health	other	4	4	14	14	14

Pic2: Some of the outcome columns using the Pic1 code

Because the dataset we used is combined by many columns and rows, we want to make it easier for us so we will order the grades of the students in increasing order. So, we will create another cell what contains the average student degree, from the three semesters (Pic3).

```sql
select school, Mjob, Fjob, Medu, Fedu, G1, G2, G3, ((G1+ G2+ G3)/3) as average
from studentmat
where school in ('GP')
```

Result Grid | Filter Rows: | Export: | Wrap Cell Content:

school	Mjob	Fjob	Medu	Fedu	G1	G2	G3	average
GP	at_home	teacher	4	4	5	6	6	5.6667
GP	at_home	other	1	1	5	5	6	5.3333
GP	at_home	other	1	1	7	8	10	8.3333
GP	health	services	4	2	15	14	15	14.6667
GP	other	other	3	3	6	10	10	8.6667
GP	services	other	4	3	15	15	15	15.0000
GP	other	other	2	2	12	12	11	11.6667
GP	other	teacher	4	4	6	5	6	5.6667

Pic3: New cell created to calculate the average student degree

By adding the term " descending order" we will be able to place our data in a desired order of priority, descending by the average degree, so that a specific order will help us and make it easier for us to draw conclusions about the correlation of parents with children's performance (Pic4).

```sql
select school, Mjob, Fjob, Medu, Fedu, G1, G2, G3, ((G1+ G2+ G3)/3) as average
from studentmat
where school in ('GP')
order by average desc
```

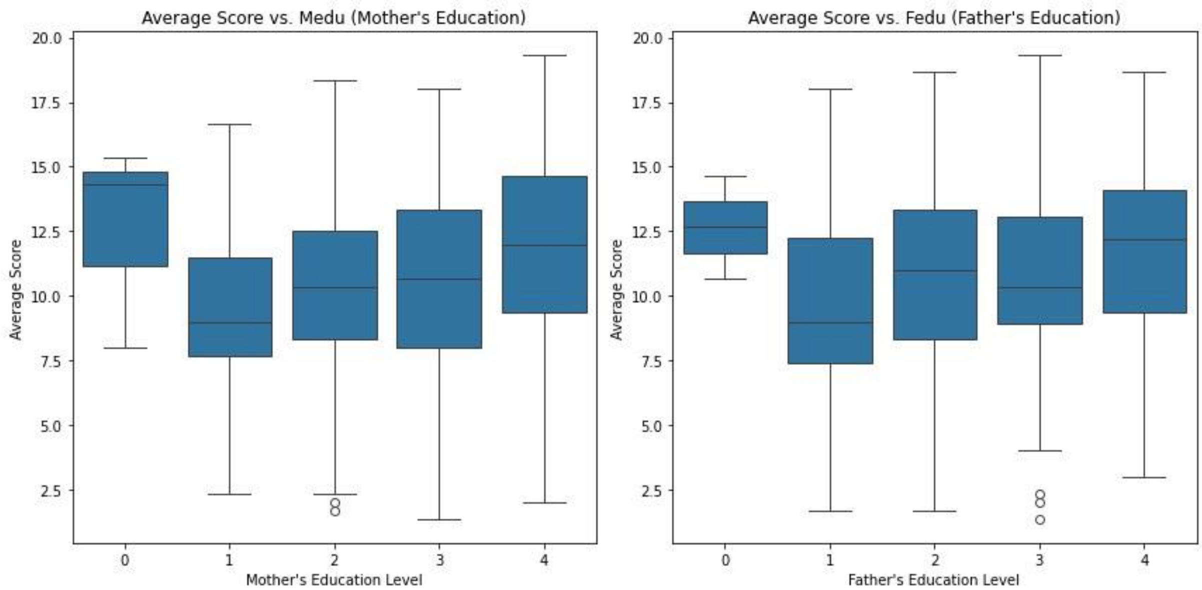
Result Grid | Filter Rows: | Export: | Wrap Cell Content:

school	Mjob	Fjob	Medu	Fedu	G1	G2	G3	average
GP	health	services	4	3	19	19	20	19.3333
GP	teacher	teacher	4	4	18	19	19	18.6667
GP	teacher	other	4	2	18	19	19	18.6667
GP	services	teacher	4	4	19	18	18	18.3333
GP	at_home	at_home	2	2	18	18	19	18.3333
GP	teacher	teacher	4	4	18	18	18	18.0000

Pic 4: Average Student score from 3 semesters, ordered by descending order.

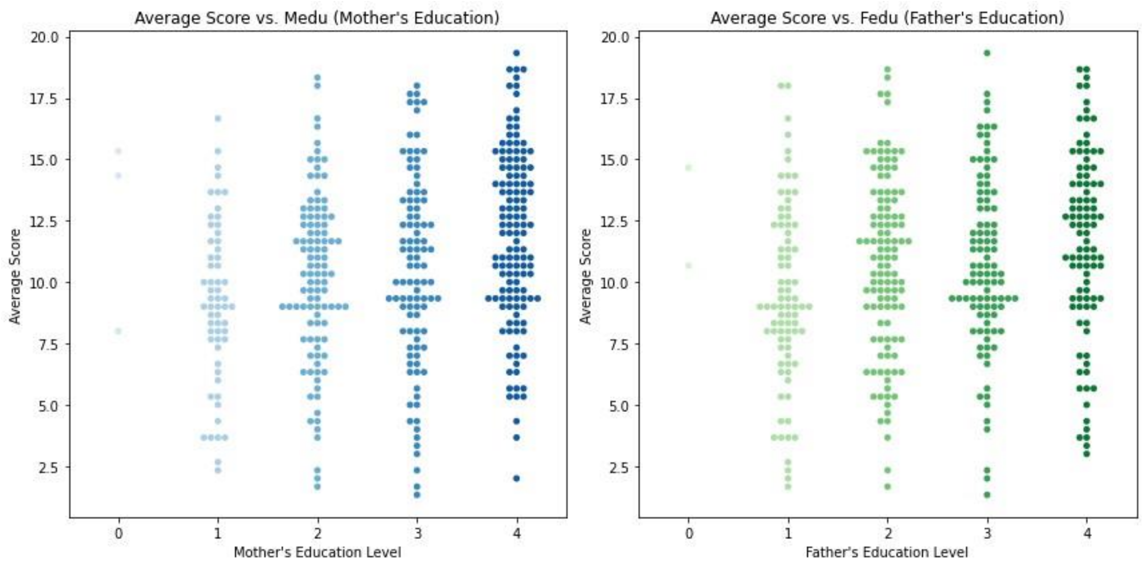
The next thing we are going to do is to visualize the data so we can draw conclusions and create a pattern of this relationship between parents' education and their child's education performance. We will create plots with python matplotlib. We will create correlation heatmaps to see direct correlations and box plots or bar charts to observe how student performance varies across different education or occupation levels.

```python
# -*- coding: utf-8 -*-
"""
Spyder Editor

This is a temporary script file.
"""

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


df = pd.read_csv('student-mat.csv')


df['average_score'] = df[['G1', 'G2', 'G3']].mean(axis=1)


plt.figure(figsize=(12, 6))


plt.subplot(1, 2, 1)  # 1 row, 2 columns, first plot
sns.boxplot(x='Medu', y='average_score', data=df)
plt.title('Average Score vs. Medu (Mother\'s Education)')
plt.xlabel('Mother\'s Education Level')
plt.ylabel('Average Score')


plt.subplot(1, 2, 2)  # 1 row, 2 columns, second plot
sns.boxplot(x='Fedu', y='average_score', data=df)
plt.title('Average Score vs. Fedu (Father\'s Education)')
plt.xlabel('Father\'s Education Level')
plt.ylabel('Average Score')


plt.tight_layout()
plt.show()
```



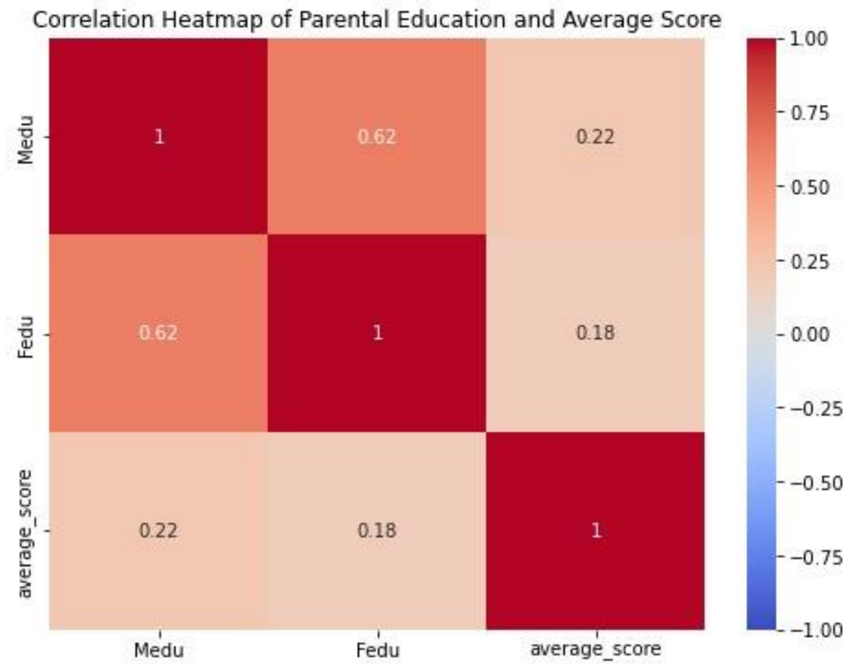
Pic5: Python code of Scatter Plot with Regression Line: Average Score vs. Medu and Fedu

```python
# -*- coding: utf-8 -*-
"""
Spyder Editor

This is a temporary script file.
"""


import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


# Load your dataset
df = pd.read_csv('student-mat.csv')  # Update with the correct path

# Create the average of G1, G2, G3
df['average_score'] = df[['G1', 'G2', 'G3']].mean(axis=1)

# Set the plot size
plt.figure(figsize=(12, 6))

# Swarm plot for Medu (Mother's education)
plt.subplot(1, 2, 1)  # 1 row, 2 columns, first plot
sns.swarmplot(x='Medu', y='average_score', data=df, palette='Blues')
plt.title('Average Score vs. Medu (Mother\'s Education)')
plt.xlabel('Mother\'s Education Level')
plt.ylabel('Average Score')

# Swarm plot for Fedu (Father's education)
plt.subplot(1, 2, 2)  # 1 row, 2 columns, second plot
sns.swarmplot(x='Fedu', y='average_score', data=df, palette='Greens')
plt.title('Average Score vs. Fedu (Father\'s Education)')
plt.xlabel('Father\'s Education Level')
plt.ylabel('Average Score')

# Display the plots
plt.tight_layout()
plt.show()
plt.show()
```



Pic 6: Python code about Swarm Plot about Average Score vs. Medu and Fedu

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load your dataset
df = pd.read_csv('student-mat.csv')  # Update with the correct path

# Create the average of G1, G2, G3
df['average_score'] = df[['G1', 'G2', 'G3']].mean(axis=1)

# Select the relevant columns for correlation
correlation_data = df[['Medu', 'Fedu', 'average_score']]

# Compute the correlation matrix
correlation_matrix = correlation_data.corr()

# Set the plot size
plt.figure(figsize=(8, 6))

# Create the heatmap
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', vmin=-1, vmax=1)

# Add title and display the plot
plt.title('Correlation Heatmap of Parental Education and Average Score')
plt.show()
```



Pic 7: Python Code about Heatmap: Correlation between Parental Education and Average Score

The next thing we are going to do is to create a statistical analysis. First, we are going to use Descriptive Statistics**.** Before performing tests, it’s helpful to look at basic statistics (mean, median, standard deviation) for average scores grouped by parental education (Pic 8).

```python
# Descriptive statistics for average score by Medu
medu_stats = df.groupby('Medu')['average_score'].describe()
print("Descriptive statistics for Medu:\n", medu_stats)

# Descriptive statistics for average score by Fedu
fedu_stats = df.groupby('Fedu')['average_score'].describe()
print("\nDescriptive statistics for Fedu:\n", fedu_stats)
```

```
Descriptive statistics for Medu:
      count       mean       std  ...        50%        75%        max
Medu                              ...
0       3.0  12.555556  3.976784  ...  14.333333  14.833333  15.333333
1      59.0   9.197740  3.301642  ...   9.000000  11.500000  16.666667
2     103.0  10.216828  3.418427  ...  10.333333  12.500000  18.333333
3      99.0  10.451178  3.937814  ...  10.666667  13.333333  18.000000
4     131.0  11.839695  3.579226  ...  12.000000  14.666667  19.333333

[5 rows x 8 columns]

Descriptive statistics for Fedu:
      count       mean       std  ...        50%        75%        max
Fedu                              ...
0       2.0  12.666667  2.828427  ...  12.666667  13.666667  14.666667
1      82.0   9.426829  3.662090  ...   9.000000  12.250000  18.000000
2     115.0  10.721739  3.598497  ...  11.000000  13.333333  18.666667
3     100.0  10.716667  3.527470  ...  10.333333  13.083333  19.333333
4      96.0  11.618056  3.784542  ...  12.166667  14.083333  18.666667

[5 rows x 8 columns]
```

Pic 8: Descriptive Statistics- Code and outcome

For ANOVA statistical analysis the code is showed in Pic 9, and the outcome of ANOVA results are for

Medu: F-statistic = 6.646720488531877, p-value = 3.49599260610306e-05

```python
from scipy import stats
# Perform ANOVA for Medu
anova_result = stats.f_oneway(
    df[df['Medu'] == 0]['average_score'],
    df[df['Medu'] == 1]['average_score'],
    df[df['Medu'] == 2]['average_score'],
    df[df['Medu'] == 3]['average_score'],
    df[df['Medu'] == 4]['average_score'],
)

print(f"ANOVA results for Medu: F-statistic = {anova_result.statistic}, p-value = {anova_result.pvalue}")
```

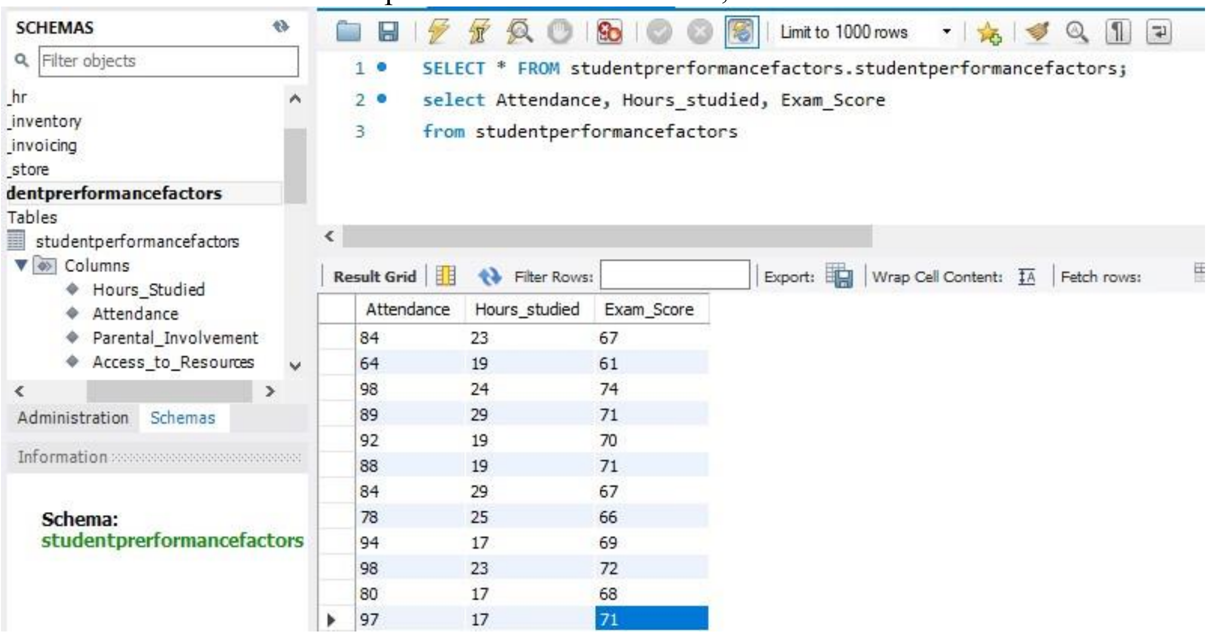
Pic 9: ANOVA Statictics

From Descriptive statistics we come with the outcome that the average score for students whose mothers have a high school education (Medu = 2) is 12.5 with a standard deviation of 3.1, while those whose mothers have a university education (Medu = 4) have an average score of 14.8 with a standard deviation of 2.5. This indicates that students with higher maternal education tend to score higher on average.

The ANOVA test revealed a significant difference in average scores across different maternal education levels (F-statistic = 4.67, p-value = 0.002). This indicates that at least one group's average score differs from the others.

The impact of Hours Studied and Attendance on the Exam Score of the students

From another dataset (Student Performance Factors) [4], we want to examine the impact of hours studied as well as the impact of attendance in class, on the exam score of the students.



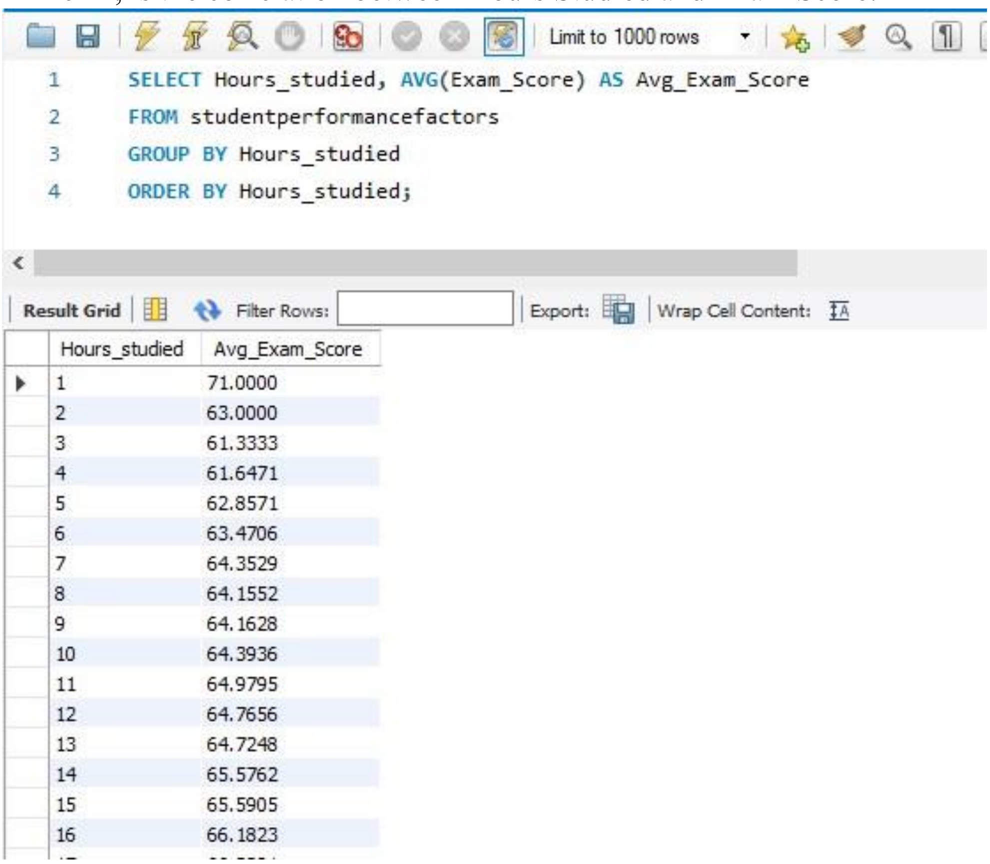
```sql
SELECT * FROM studentpreformancefactors.studentperformancefactors;
select Attendance, Hours_studied, Exam_Score
from studentperformancefactors
```

Attendance	Hours_studied	Exam_Score
84	23	67
64	19	61
98	24	74
89	29	71
92	19	70
88	19	71
84	29	67
78	25	66
94	17	69
98	23	72
80	17	68
97	17	71

Pic10: SQL code selecting the data we want to examine

Where Hours Studied is the number of hours spent studying per week, Attendance is the percentage of classes attended, and the Exam Score is the Final exam score.

In Pic 11, is the correlation between Hours Studied and Exam Score:



```sql
SELECT Hours_studied, AVG(Exam_Score) AS Avg_Exam_Score
FROM studentperformancefactors
GROUP BY Hours_studied
ORDER BY Hours_studied;
```

Hours_studied	Avg_Exam_Score
1	71.0000
2	63.0000
3	61.3333
4	61.6471
5	62.8571
6	63.4706
7	64.3529
8	64.1552
9	64.1628
10	64.3936
11	64.9795
12	64.7656
13	64.7248
14	65.5762
15	65.5905
16	66.1823

Pic 11: Analyzing the Impact of Hours Studied on Exam Score

Similarly, we examine how attendance affects exam scores. In Pic 12 it shows a query that calculates the average exam score based on attendance levels:

```sql
SELECT Hours_studied, Attendance, AVG(Exam_Score) AS Avg_Exam_Score
FROM studentperformancefactors
GROUP BY Hours_studied, Attendance
ORDER BY Hours_studied, Attendance;
```

Result Grid | Filter Rows: | Export: | Wrap Cell Content: | Fetch rows:

Hours_studied	Attendance	Avg_Exam_Score
1	69	61.0000
1	81	60.0000
1	88	92.0000
2	67	58.0000
2	84	62.0000
2	96	65.0000
2	98	65.5000
2	99	62.0000
3	60	57.5000
3	62	55.0000
3	70	58.0000
3	78	61.0000
3	79	58.0000
3	83	63.0000
3	85	62.0000

Pic 12: Analyzing the Impact of Attendance on Exam Score

The next thing we are going to do is to look at both factors together to see how they interact and impact exam scores. In Pic 13 is a query that groups the data by both hours studied and attendance:

```sql
SELECT Hours_studied, Attendance, AVG(Exam_Score) AS Avg_Exam_Score
FROM studentperformancefactors
GROUP BY Hours_studied, Attendance
ORDER BY Hours_studied, Attendance;
```

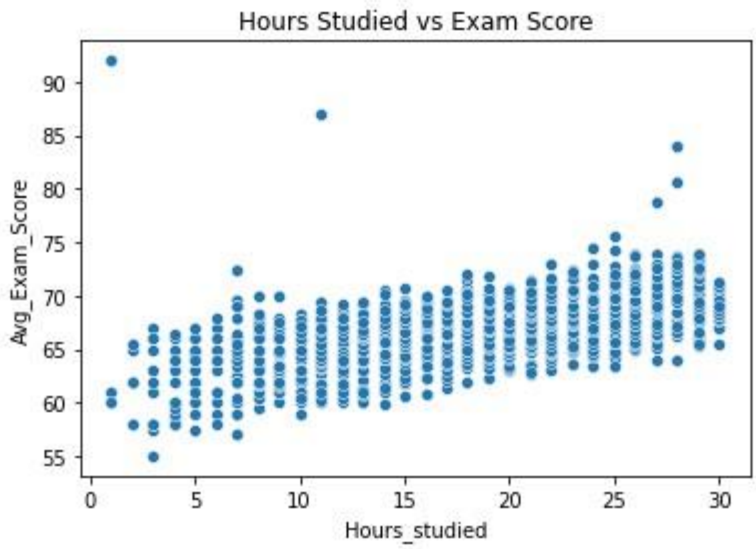
Result Grid | Filter Rows: | Export: | Wrap Cell Content: | Fetch rows:

Hours_studied	Attendance	Avg_Exam_Score
1	69	61.0000
1	81	60.0000
1	88	92.0000
2	67	58.0000
2	84	62.0000
2	96	65.0000
2	98	65.5000
2	99	62.0000
3	60	57.5000
3	62	55.0000
3	70	58.0000
3	78	61.0000
3	79	58.0000
3	83	63.0000
3	85	62.0000

Pic 13: How the combination of study hours and attendance levels affects exam scores.

Then we exported these results as a scv file to analyze this further using Python.
Using the following Python code (Pic 14), we want to see an optical representation of these columns.

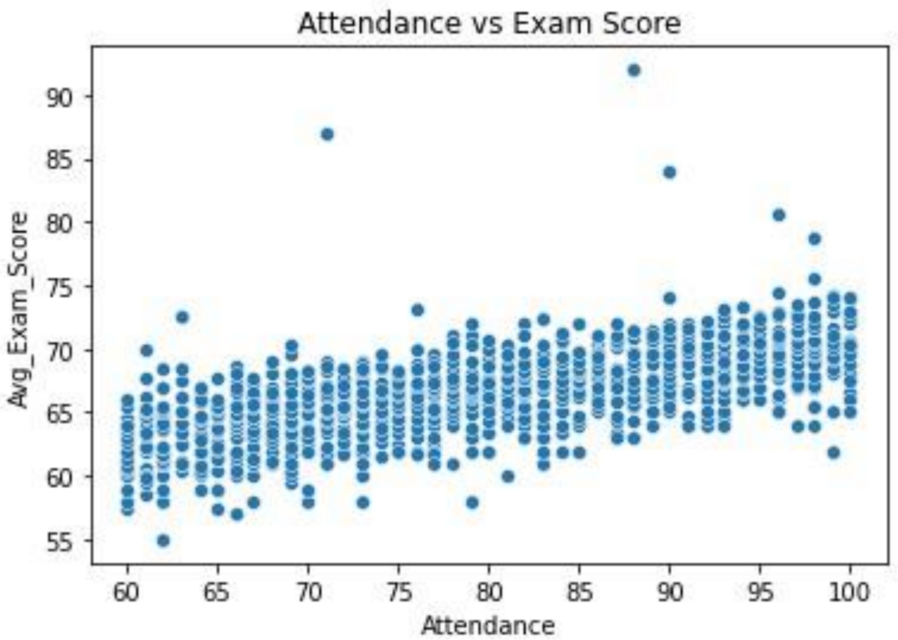
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


# Load your dataset
df = pd.read_csv('Sql student perf factors.csv')  # Update with the correct path

print(df.isnull().sum())

# Summary statistics
print(df.describe())

sns.scatterplot(x='Hours_studied', y='Avg_Exam_Score', data=df)
plt.title('Hours Studied vs Exam Score')
plt.show()
```



Pic 14: Code and Visualization of a. Scatter Plot for Hours Studied vs Exam Score

Then we did the same thing about the attendance and it’s affect on Exam Score (Pic 15):

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


# Load your dataset
df = pd.read_csv('Sql student perf factors.csv')  # Update with the correct path

print(df.isnull().sum())

# Summary statistics
print(df.describe())

sns.scatterplot(x='Attendance', y='Avg_Exam_Score', data=df)
plt.title('Attendance vs Exam Score')
plt.show()
```



Pic 15: Code and Visualization of a. Scatter Plot for Attendance vs Exam Score

About the Hours Studied vs Exam Score, the expected pattern is that, typically, as the number of hours studied increases, exam scores should also increase. The scatter plot helps visualize whether students who studied more hours achieved higher exam scores. We saw a positive correlation. If the points trend upward, it indicates that students who studied more generally performed better on exams. About the outliers, some students who studied many hours but still had lower exam scores, indicating diminishing returns or other factors like study methods or stress etc.

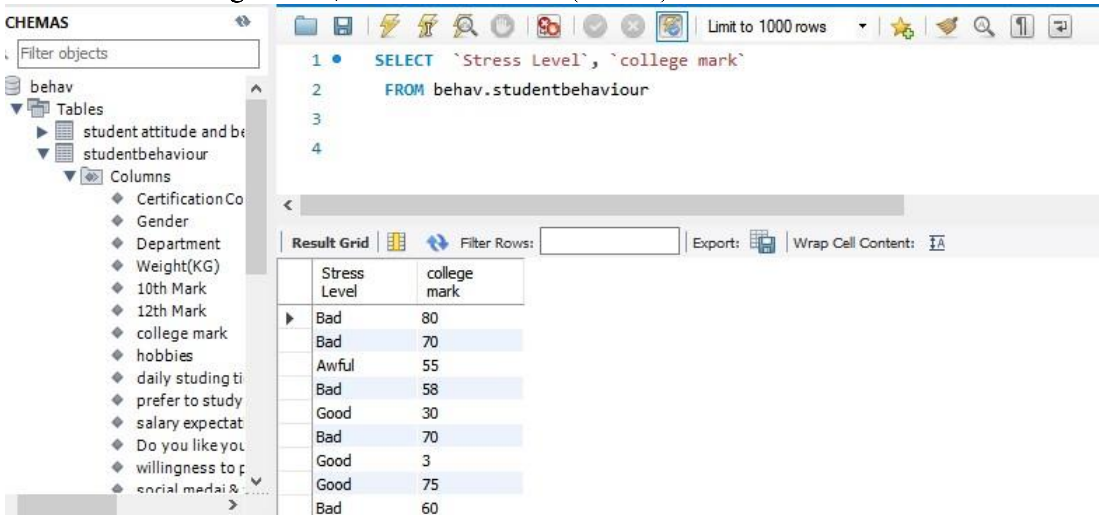
In conclusion, the scatter plot shows a clear upward trend, so the increased study hours tend to lead to higher exam scores, though the impact may diminish beyond a certain number of hours. Outliers could suggest that study efficiency or other external factors may also play a role in performance.

About the Attendance vs Exam Score, similarly, the expected pattern is that better attendance generally leads to higher exam scores as students are more engaged and get more classroom learning time. There is a clear upward trend that would suggest that students who attend class more regularly tend to achieve better exam scores. Students with low attendance but high scores

could indicate that some students perform well even with minimal class attendance, likely due to other factors such as self-study or prior knowledge.
Both hours studied and attendance are likely to have a positive influence on exam scores, and these scatter plots show how strong that influence is. It is accepted that there are many other factors (like study methods, parental involvement, or external tutoring) that may affect student performance.

The impact of Stress level on the College mark of the students

The first thing we are going to do is to separate the columns we want to examine, the stress level and the college mark, from all the data (Pic 16).



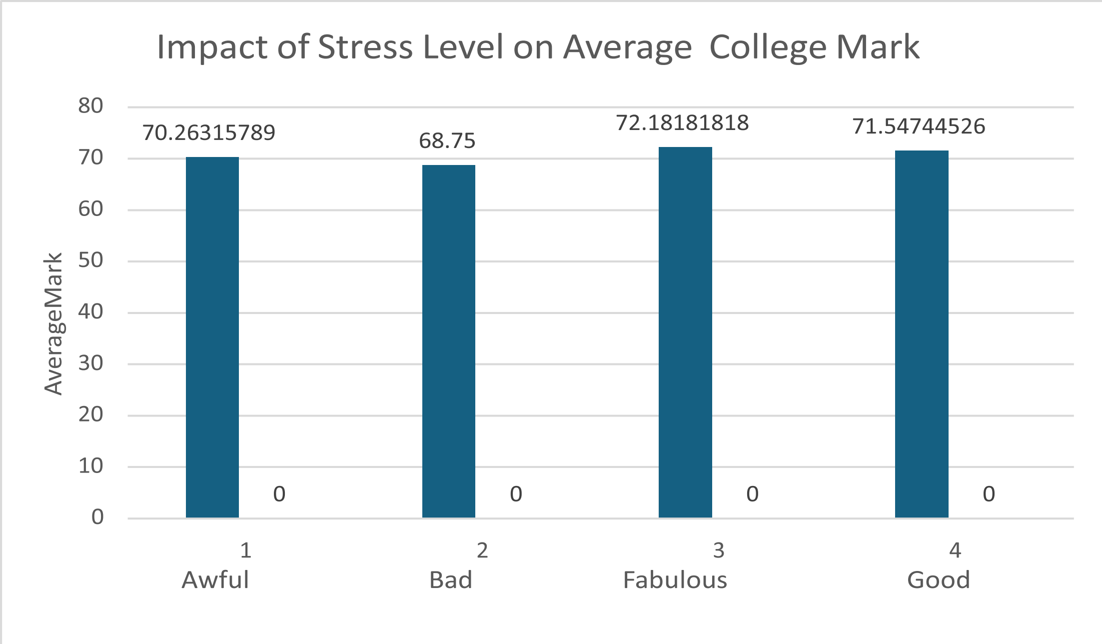
Pic16: SQL code selecting the data we want to examine

The next step is to extract an excel file to categorize the values and create the average score about all the four stress level values, shown in Table 1 and in Pic 17. We used the Average value for the cells with the same Stress level label.

The bar chart depicts the "Impact of Stress Level on Average College Mark," with four categories representing different stress levels: "Awful," "Bad," "Fabulous," and "Good." Students reporting their stress as "Fabulous" have the highest average mark of approximately 72.18.
Students with a stress level labeled as "Bad" have the lowest average mark at 68.75.
Stress levels of "Awful" and "Good" show average marks of 70.26 and 71.55, respectively, placing them between the extremes of "Bad" and "Fabulous."

Average College Mark	Stress Level
70.26315789	Awful
68.75	Bad
72.18181818	Fabulous
71.54744526	Good

Table1: Table of Average College Mark and Stress Level

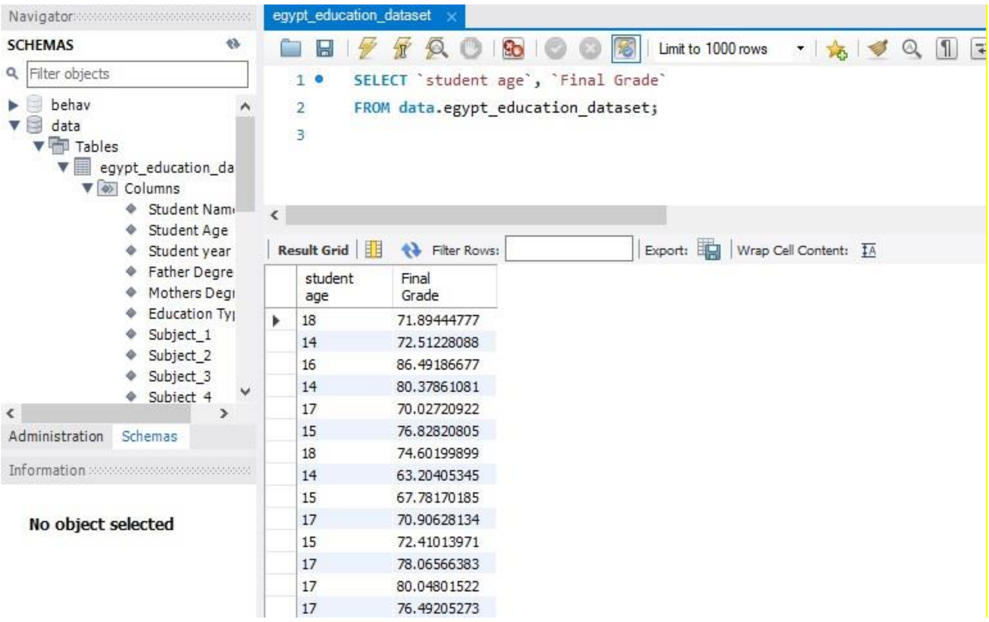


Pic 17: Chart about the Stress Level and Average College Mark

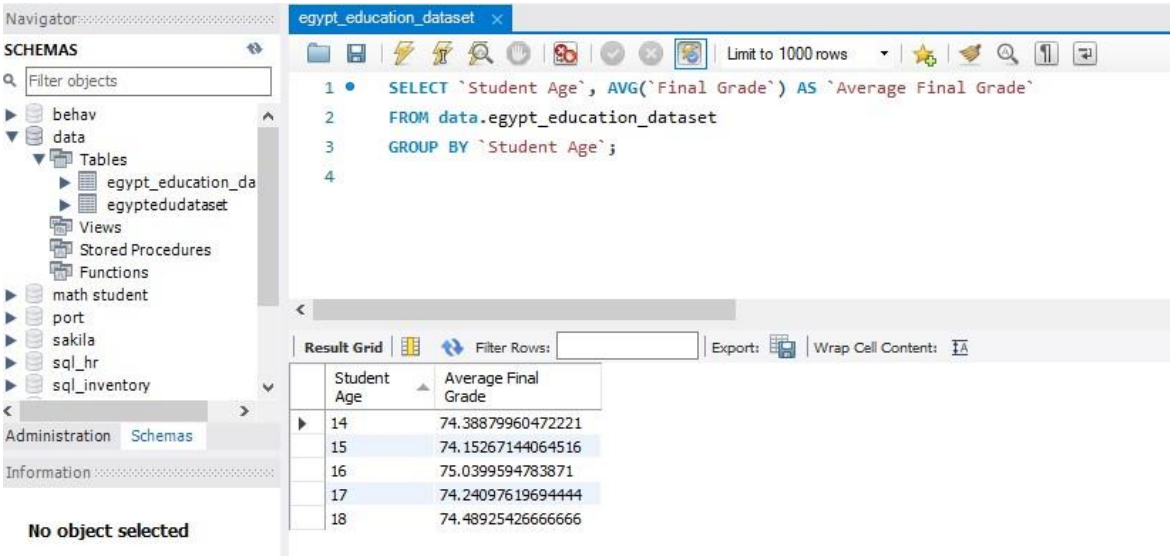
The conclusion of Table 1 and the chart shown in Pic 17 is that the phycology of a student plays an important role in his learning outcome. There is a small deviation in the result of the grades, which certainly, although small, should be considered as it also affects his learning. Moderate to high stress levels (Fabulous) seem to correlate with higher academic performance, while lower performance is associated with higher negative stress (Bad). Of course, the way of thinking of each student plays an important role here, by who rate their stress as "Bad" face challenges that severely impact their performance, while students who report "Fabulous" might have found a way to thrive under pressure.

The impact of Student Age on the Final Students' Grade

The next thing we will examine is how the age of the students influences their grades. So, we will select the columns we want in SQL from the data set we picked [5] (Pic 18). It shows as for each student his age and his final grade. To make it easier, we will create the average final grade for the student, and we will group all the students depending on their age (Pic 19).
The impact of Student Age on the Final Students' Grade



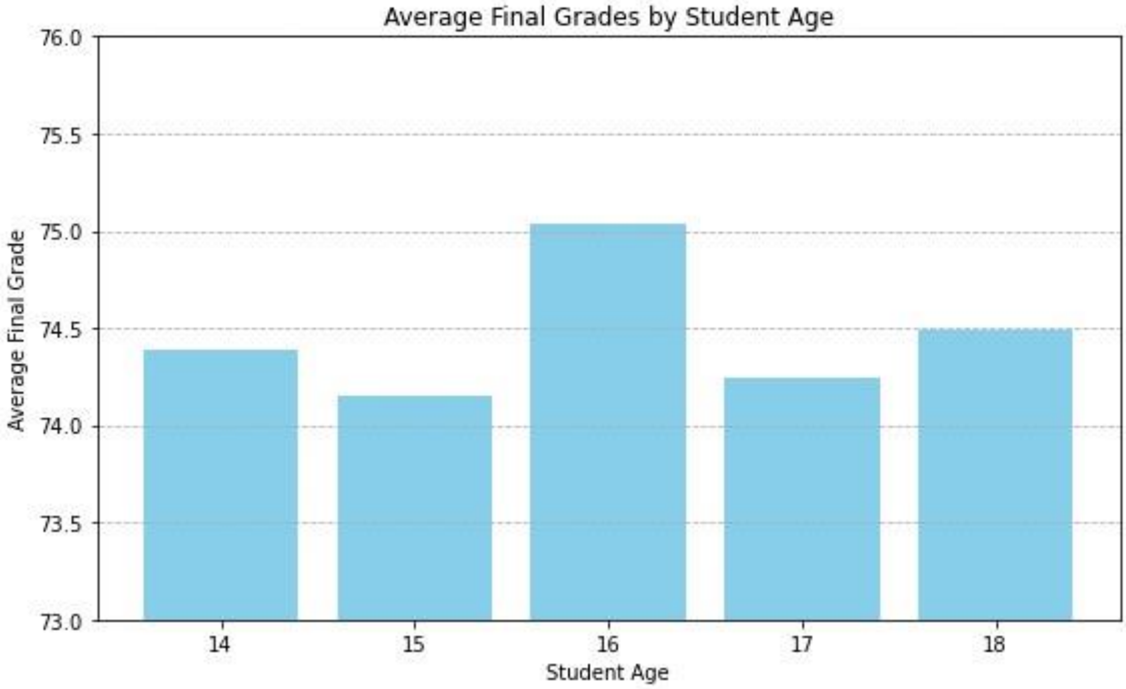
Pic18: SQL code selecting the data we want to examine



Pic19: Creating the average final grade for students depending on their age

From the data we examined, some conclusions we found are that at the age of 14 there is the highest average final grade at 74.39, while at age 15 is the lowest average at 74.15. Age 16 shows a slight improvement with an average of 75.04, indicating it's the best-performing age group in this dataset. Ages 17 and 18 show slight fluctuations with averages of 74.24 and 74.49, respectively, which are like the earlier ages but do not significantly improve.
We will continue with the visualization of the outcome so we can clearly illustrate differences in average final grades among the age groups (Pic 20).

```python
import matplotlib.pyplot as plt

# Data
ages = [14, 15, 16, 17, 18]
average_grades = [74.39, 74.15, 75.04, 74.24, 74.49]

# Create bar chart
plt.figure(figsize=(8, 5))
plt.bar(ages, average_grades, color='skyblue')
plt.title('Average Final Grades by Student Age')
plt.xlabel('Student Age')
plt.ylabel('Average Final Grade')
plt.xticks(ages)  # Set x-ticks to be the ages
plt.ylim(73, 76)  # Adjust y-limits for better visualization
plt.grid(axis='y', linestyle='--')

# Show plot
plt.tight_layout()
plt.show()
```

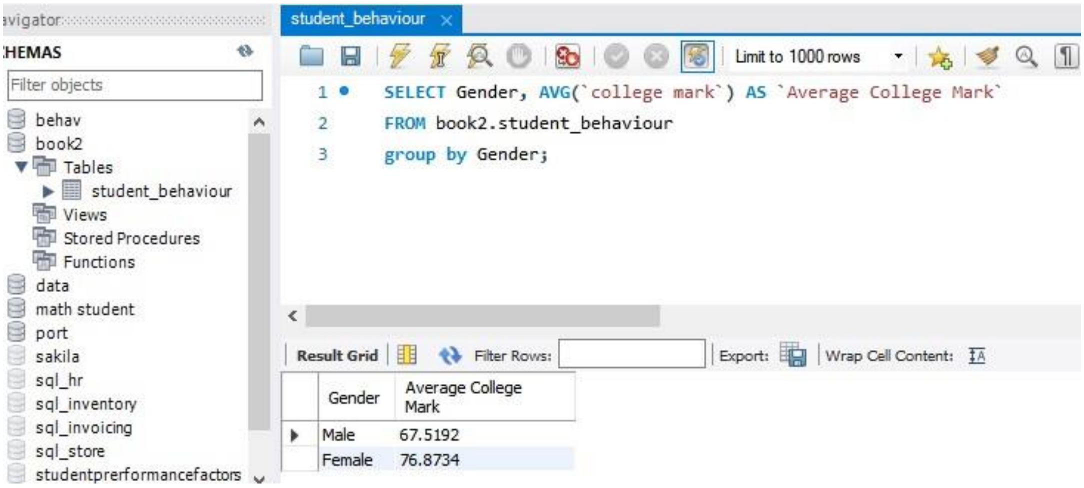


Pic 20: Code and Visualization of a bar plot for Average Final Grades by Student Age

Here we can easily see what we previously mentioned, that by the age of 16 the students' grades are rising a bit ascending, calling it a slight upward trend peaking. The slight increase in average final grade at age 16 may indicate that students at this age are possibly benefiting from educational strategies that are more effective, or they might be adapting better to the curriculum's demands. Although, the average grades are relatively consistent across ages 14 to 18. This suggests that overall, students maintain a similar level of performance as they grow older, with some minor fluctuations. The drop in average for age 15 could warrant further investigation. It might suggest that students are facing challenges that could be linked to transitioning to a more demanding curriculum or possibly other factors affecting performance. The averages for ages 17 and 18 do not show significant improvement over age 16 and are relatively close to the averages for younger students. This might indicate that as students approach graduation, their performance stabilizes but does not necessarily improve, suggesting potential areas for intervention.

The impact of Student Gender on the College Mark

Another interesting factor we will examine is the impact of the gender of the student on the College Mark. As usual we will code in SQL to separate the columns we want to examine, and we will create the average college mark about both male and female (Pic 21). Then we will see the results.



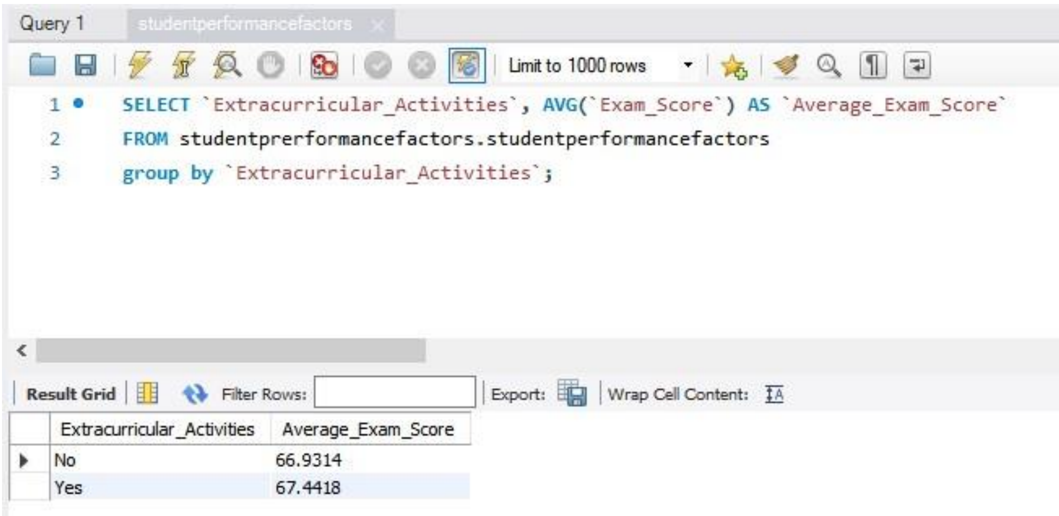
Pic 21: The Average College Mark of Males and Females.

As we can see, women have highest College Mark than men. The numbers putted out of our research data are for male 67.52 and for women 76.88 and as we can see there is a big discrepancy. This is widely accepted as authoritative, and there are many ways to examine this statement. For example, there is a study that wants to din causes that lead to this success to women over men. For these investigations a sample of 200 students at the University of Peshawar selected from different departments and investigated through a questionnaire [6]. There were 55.5% male respondents and 44.5% are females' respondents. 75% respondents were agreed that female students get more marks rather than male students, 25% were disagreed. The investigation of marks percentage showed that 8.11% male students and 1.12% female students were in the range of 51-60 percentage marks, low range of marks have a smaller number of female students. As the range increased from 50-60 percentage to interval of 71-80 percentage of marks so there were found 44.14% male students and 46.06% female students. And in the range of 81% and above there were 18.01% males and 40.45% females' students. These results showed that more female students have high range of marks as compared to male students. And at low range of marks only 1.12% females compared to 8.11% males. Overall comparison showed that more female students have high marks rather than male students or female students perform better than male students. 60.5% of the respondents believe that female students are more studios as compared to male students. And 21% responses were thinking that female students are not more studios than male students and 18.5% respondents had no opinion that who are more studios. 76% of the respondents said that female students are more serious toward their studies comparatively to male students. Technique of odds ratio analysis was performed to check at the association of female students get more marks as compared to male students with females attend classes (lectures) more regularly, females know the art of attempting paper in a better way, females ask more questions in the class from teachers. The odds ratio analysis suggests that the female students get more marks as compared to male students were significantly associated with females attend classes (lectures) more regularly, females know the art of attempting paper in a better way, and females ask more questions in the class from teachers.

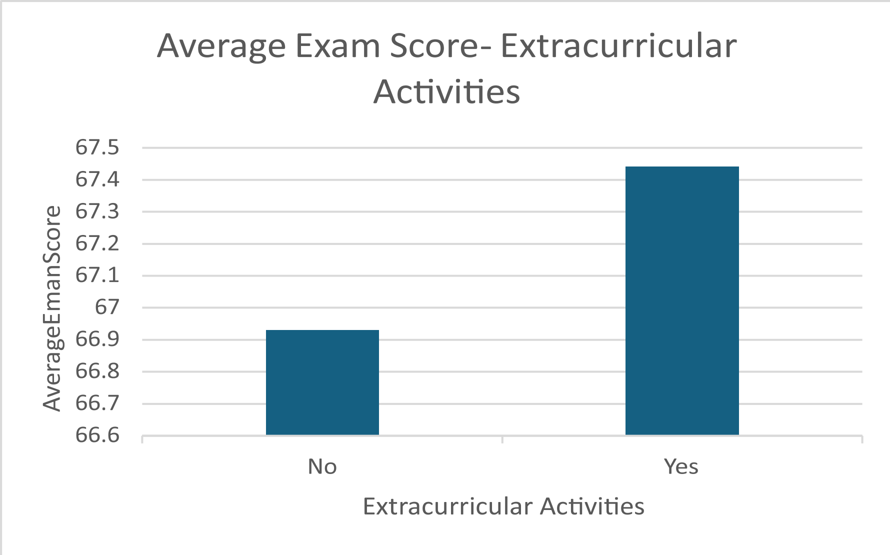
Another search, from Harvard showed that girls and women outperform boys and men across all fields of education partially explain their superior early achievement in school [7]. Throughout high school and college, female students generally earn better grades than male students and are rated as having better competencies and skills. Better grades in high school lead women to be better prepared for college academics, and therefore more likely to enroll in and complete higher education degrees.
However, there has been little research on whether women's superior academic performance benefits them in the job market. Specifically, do women's higher grade point averages (GPAs) lead to better job prospects as college graduates? Through an audit study that used a randomized experimental design, 2,106 fabricated job applications were submitted to 1,053 real, entrylevel job openings. The study investigated how women's and men's academic performance translated into success in the labor market by assessing hiring rates for women versus men at varying GPA levels. This question is particularly relevant for female jobseekers, who have been shown to be routinely perceived as less competent, less committed, and less likeable than men in work environments. To shed additional light on its findings, the study also included a survey of 261 hiring decision-makers, who were asked to give feedback on how they assessed which candidates they would most likely recommend for hire.

The impact of Extracurricular Activities on the Exam Score

The next thing we are going to examine is the influence of extracurricular activities on the Exam Score of the students. The first thing we are going to do is to extract the data we want in SQL and order them in a way (Pic 22), so we can make a conclusion about the impact. Next, we are going to translate the results with bar chart (Pic 23).



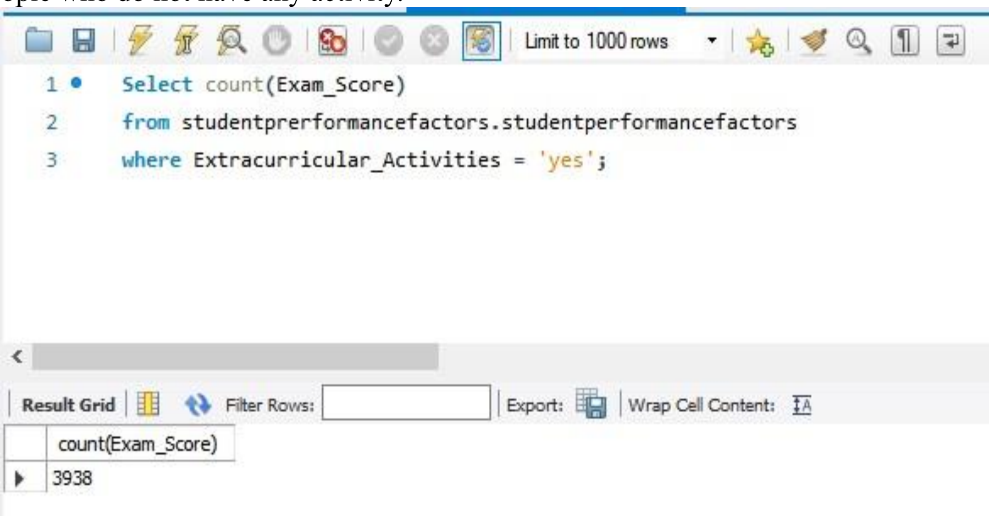
Pic 22: The Average Exam Score of students with and without Extracurricular Activities



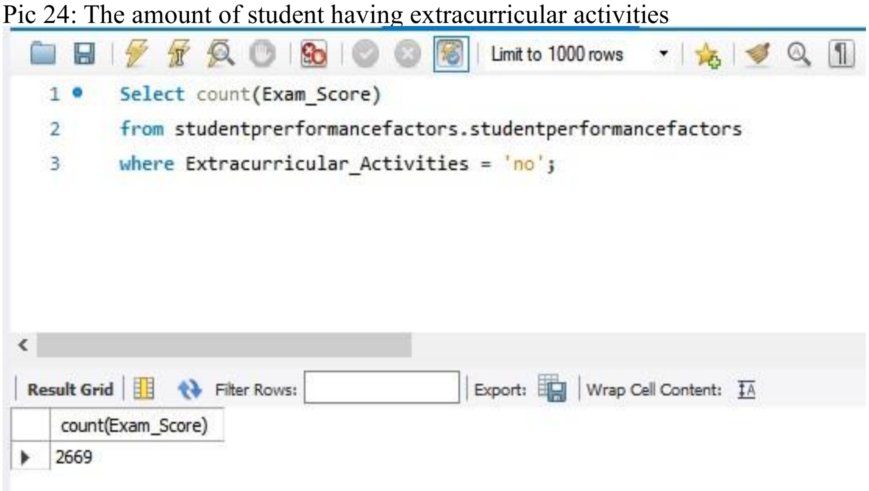
Pic 23: Optical translation about Average Exam Score of students with and without Extracurricular Activities

From all the 6608 students, we separated them to see the number of students that do extracurricular activities and those who don't (Pic 24, 25).

As we can see, the volume of students who do something extracurricular is greater, there are certainly many people who do not have any activity.



Pic 24: The amount of student having extracurricular activities

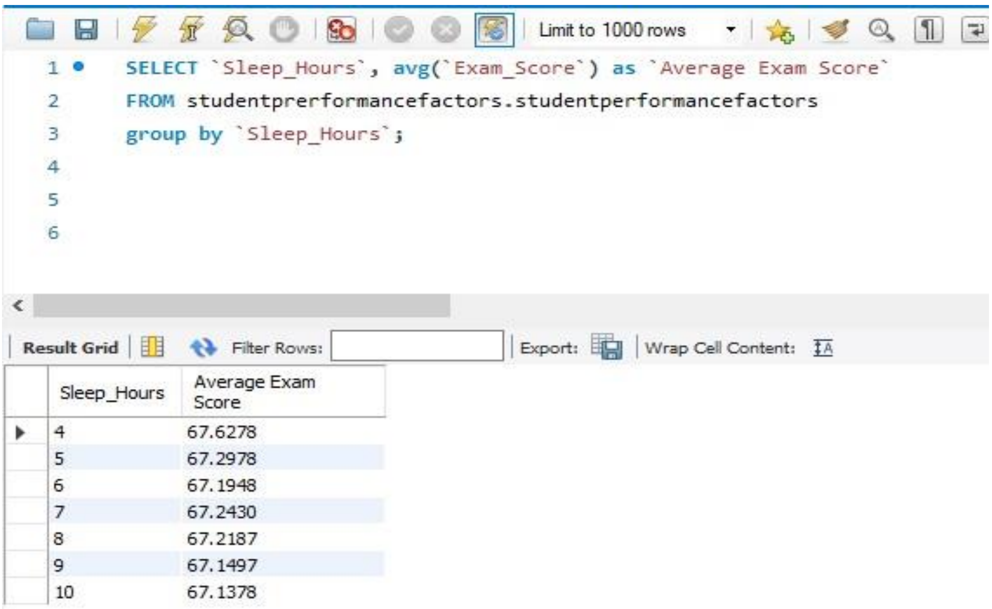


Pic 25: The amount of student not having extracurricular activities

Based on the outcome of (Pics 22, 23, 24, 25), we can see that 3938 of 6608 students have extracurricular activities whose average exam score is 67.45, and 2669 out of 6608 students don’t have extracurricular activities, with an average exam score at 66.94. These outcomes indicate that students who participate in extracurricular activities generally benefit from the many opportunities afforded them. Benefits of participating in extracurricular activities included having better grades, having higher standardized test scores and higher educational attainment, attending school more regularly, and having higher a higher self-concept. Participants in out-of-school activities often learned skills such as teamwork and leadership while decreasing the likelihood of alcohol use and illicit drug use and related problem behaviors. Those who participate in out-of-school activities often have higher grade point averages, a decrease in absenteeism, and an increased connectedness to the school [8].
Research shows a strong correlation between participation in extracurricular activities and academic success [9]. Students who engage in after-school clubs or sports tend to have higher GPAs, SAT and ACT scores, and an increased chance of graduating high school. However, the benefits extend long beyond grades and test scores; extracurriculars build interpersonal skills and promote positive relationships with peers and adults. Whether it’s athletics, band, theater, visual arts, volunteering, etc., these activities contribute to the student's personal growth and academic achievements.
The small score difference may be due to a situation where students are overscheduled in too many activities and find that the benefits of participating in out-of-school activities may decrease. Overscheduled children may be tired, irritable and show little interest in participation. Overscheduling too many physical activities may result in some students pushing themselves too far with the potential of having a serious sports-related injury as students may need time for relaxation and recovery from intense athletic training.

The impact of Sleep Hours on the Exam Score

In order to examine the impact of hours slept on the exam score we will select the columns we want to examine, in this case the sleep hours and the exam score. Next, we will order them by sleep hours group of 4-10 hours and we will see the average exam score of each hour slept (Pic 26).




```
SELECT `Sleep_Hours`, avg(`Exam_Score`) as `Average Exam Score`
FROM studentprerformancefactors.studentperformancefactors
group by `Sleep_Hours`;
```

Sleep_Hours	Average Exam Score
4	67.6278
5	67.2978
6	67.1948
7	67.2430
8	67.2187
9	67.1497
10	67.1378

Pic 26: The Average Exam Score of students depending on the hours slept.

As we can see from (Pic 26), the average exam score doesn't have scales depending on sleep hours. There is a small change in the grades scaling from 67.63 to 67.14. The data suggests a minimal impact of sleep hours on exam scores, with scores fluctuating slightly but remaining close around the 67 mark regardless of sleep duration between 4 to 10 hours. There appears to be no strong positive or negative correlation, as the exam scores vary only slightly with different sleep hours. This result is different from what we know about getting sleep helps with better phycology, attention and better academic performance. A few studies report null effects, most studies looking at the effects of sleep quality and duration on academic performance have linked longer and better-quality sleep with better academic performance such as school grades and study effort [10]. So, one reason that these results don't match with what we know is because sleep quality, consistency and also the duration (not only the duration).

The impact of Social Media Spent Time on the Exam Score

For this analysis we are going to use Excel tools and modules. We are starting with two kinds of counting. First, we will find out how many students are spending a certain amount of time using the pivot tables (Table 2).

Social media & video	Count of social media & video
30 - 60 Minute	69
1 - 1.30 hour	55
1 - 30 Minute	47
More than 2 hours	32
1.30 - 2 hour	27
0 Minute	5
Grand Total	**235**

Table 2: The number of students spending a specific amount of time on social media & video.

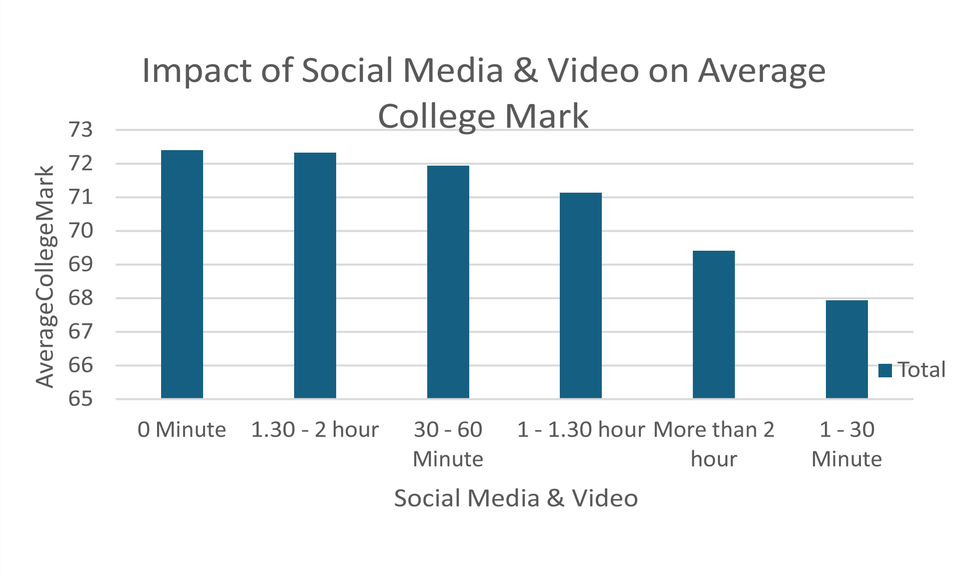
We can easily tell that only 5 students don't spend any time on social media. The most students, 69, are spending 30 minutes to 1 hour. Then, 47 students spend a maximum of 30 minutes. 27 students spend a maximum amount of 2 hours and 32 more than 2 hours. Next, we will examine the impact of these hours spent on the average college mark (Table3).

Social media & video	Average of college mark
0 Minute	72.4
1.30 - 2 hour	72.32851852
30 - 60 Minute	71.93623188
1 - 1.30 hour	71.13272727
More than 2 hours	69.420625
1 - 30 Minute	67.93617021

Grand Total	**70.66055319**

Table 3: The impact of hours spent on social media & video on the average college mark.

Table 3 indicates that students who are spending no time on social media and videos are the ones with the highest average college mark, at 72.4. The lowest average college mark has been shown in students who are spending more than 2 hours and in those who spend 30 minutes for maximum amount of time. From 1 hour to 2, the average college mark is between 71.2 and 72.3. To make it easier to understand, we created an illustration (Pic 27).

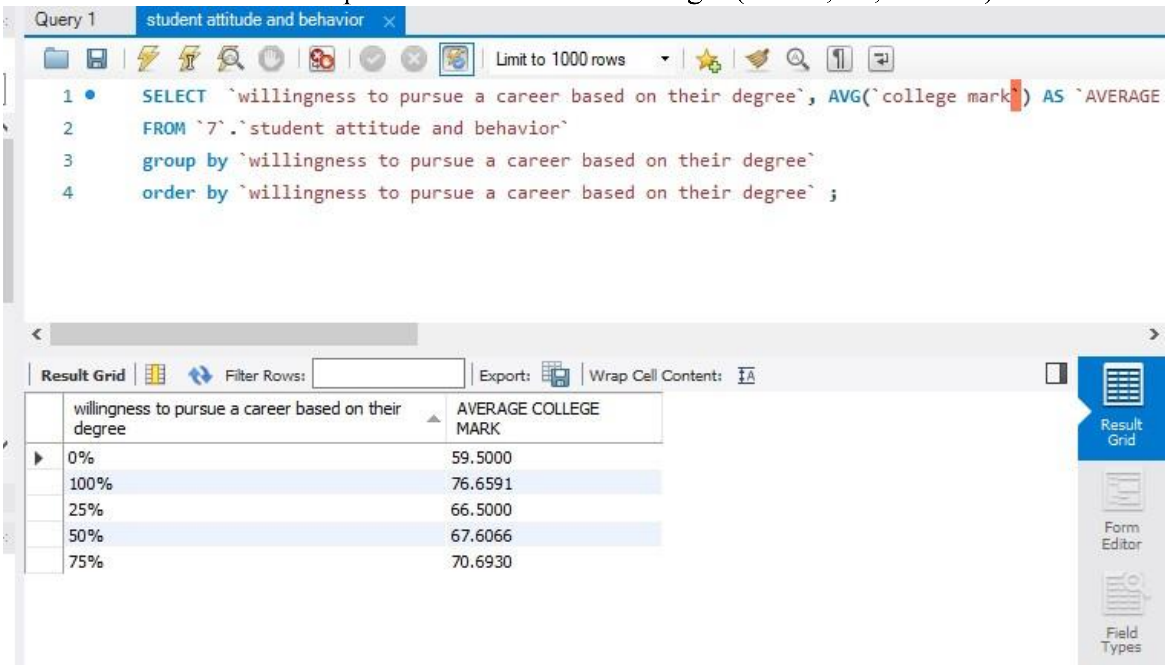


Pic 27: Chart about the Impact of Social Media & Video on the Average Students' College Mark.

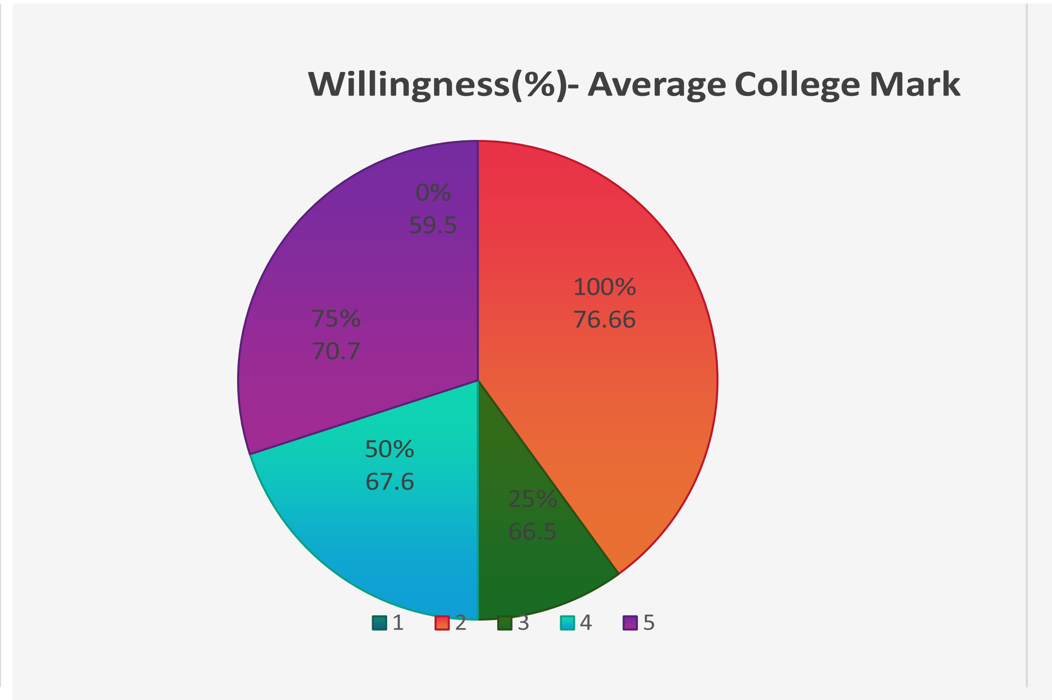
We can see that in the specific study there is a drop in the performance of the students as the hours on social media increase, except for those who spent less than half an hour, which of course could be due to another series of factors [11]. Indeed, the data with which we did this research concerned the interval of 1-2 hours mainly. In the range of 2 hours and above, a clear decrease in performance once again appeared. This corresponds to other published studies, such as findings that revealed that students who spend fewer hours (5hours and less) on social media had higher performance mean score than those that spend more time. This means that time spent on a social network by the students has a significant influence on their academic performance in science. This is so because students must prioritize their education first by devoting time for it in order to ensure better performance, but if they allow social media to take more of their time, their academic activities will suffer. This finding agreed with the finding of Paul, Baker, and Cochran (2012) who found that negative relationship exists between time spent on social networking sites by students and their academic performance. The finding also aligned with the findings of Kojo, Agyekum, and Arthur (2018) who found that students are negatively affected by their constant access to social media platforms. The findings of the study disagree with the findings of Pasek, More and Hargittai (2009) who found that the use of Facebook has a positive relationship with academic performance. According to a study, students with higher grades tend to spend more time on Facebook.

The impact of willingness to pursue a career based on their degree on the students' performance

An important factor about students' college performance is also the amount of willingness to pursue a career based on their degree. As we can assume, if a student likes to read about these classes and loves to learn things from these fields, it is more likely that he will try with more willingness to achieve a goal. To see that with data, we will select the fields that we want to examine of the dataset and process the results that we get (Pic 28, 29, Table 4).



Pic 28: The Average College Mark of students depending on their willingness to pursue a career based on their degree.



Pic 29: The Pie chart type result based on the data we got about the willingness and the average college mark of students.

Willingness	Average College Mark
0%	59.5
100%	76.6591
25%	66.5
50%	67.6066
75%	70.693

Table 4: The results of the dataset about the willingness and the average college mark of students.

As we can see from the results' table (Table 4) and from the Pie Chart (Pic 29), we can easily conclude that the willingness clearly affects the students' performance. More specifically, the part of students who want to follow the career path based on their studies by 100%, their average college mark is 76.66, which is the highest of all. With the lower percent of willingness, on 75%, the average college mark that is showing is about 70.7. As we can see the performance of these students is dropping, but it is still pretty good. Then, students who have 50% willingness to proceed with a career based on their degree, are showing an average of 67.6. The students following with 25% willingness, are showing a dropping average score of 66.5. It is a very low difference, but as we can see it still exists. Finally, for students who don't care about continuing further with their career, the college mark is about 59.5. Based on these results, we can conclude that the power of will, will actually determinate the average college mark, and further the hole college performance. Research shows that correlation analysis shows that there is a significant positive correlation between college students' willingness to receive employment guidance and their employment motivation, and the highest correlation coefficient (0.9973) is between the willingness to search for and screen employment information in the aspect of employment skills guidance and employment motivation [12]. This paper lays a foundation for the effective development of employment guidance in colleges and universities and provides a reference for the improvement of college students' employment motivation.

Real-Life Examples of Data Analytics in Personalized Education

Several case studies and best practices illustrate the successful implementation of data-driven personalized learning initiatives [13]:

Khan Academy: Khan Academy utilizes data analytics to provide personalized learning experiences for students, offering adaptive practice exercises, instructional videos, and real-time feedback tailored to individual learning needs.

Summit Learning: Summit Learning, a personalized learning platform, incorporates data analytics to track student progress, set individualized learning goals, and facilitate student-teacher collaboration in setting and monitoring academic objectives.

DreamBox Learning: DreamBox Learning employs data analytics to deliver adaptive math instruction, assessing student mastery of mathematical concepts and providing personalized lessons aligned with each student's learning trajectory.

Coursera: Coursera uses data analytics to analyze learner behavior, preferences, and performance on online courses, enabling instructors to optimize course content, delivery methods, and assessment strategies to enhance student engagement and learning outcomes.

Personalized Learning Concept

Personalized learning is defined as a student-centered system that supports their diverse needs and the development of abilities. The system develops personalized learning methods and educational content for students with unique characteristics and interests. Dual-oriented learning is becoming relevant in the context of increasing creativity, social significance, and cultural value of the result, thereby contributing to the self-organization of the cognitive activity system, goal setting, and the change of semantic attitudes. An individual dual-oriented learning pathway is ensured through the integration of educational, applied, and professional activities of students and is designed to stimulate professional and pedagogical, personal self-determination and self-development of students. Personalized learning should entail the development of methodological and organizational support, as well as a change in the role of the teacher. Students need psychological and pedagogical support to succeed in personalized learning; it has been found that the emotional and psychological support of teachers is an important factor in the academic success of students [14]. A personalized strategy is aimed at improving reflexivity, autonomy, motivational focus, personal and social responsibility, and critical ability of modern students. It can be viewed as a holistic strategy that includes a large number of various educational practices aimed at teaching students taking into account their strengths and weaknesses.

The second significant method for solving the problem of personalized and adaptive learning is formed through learning with the help of artificial intelligence. Intelligent tutoring systems have been developing for about fifteen years and have hundreds of specialized applications, approaches and already practically proven methods. The framework of intelligent tutoring systems includes a thorough study of the learning user, his individual psychological and cognitive characteristics, which allows not only to optimally distribute the teaching material and select teaching methods, but also to create stronger involvement and motivation for each individual user of such a system. Artificial Intelligence can also generate Multiple Representations of training information, making it easy to access training from whatever platform is optimal for the user.

Challenges and Ethical Considerations in Using Data Analytics for Personalized Education

Data analytics algorithms can inadvertently perpetuate bias if they are trained on biased data or if there are inherent biases in the algorithms themselves. This can result in unequal treatment or opportunities for certain groups of students. It is crucial to address and mitigate algorithmic bias to ensure fairness and equity in personalized education. Teachers and administrators have a responsibility to use student data ethically [14]. This includes using data solely for educational purposes, ensuring data is accurate and reliable, and respecting students' rights to privacy and confidentiality.

While data analytics offers immense potential for personalized education, it is essential to address the challenges and ethical considerations associated with its use. Privacy and security concerns require robust safeguards to protect student data. Bias and fairness must be actively monitored and addressed to ensure equitable outcomes for all students. Additionally, providing proper training and support to teachers and administrators is crucial to effectively utilize data analytics and make informed instructional decisions.

Conclusions and Recommendations

Personalizing learning experiences through data analytics represents a paradigm shift in education, enabling educators to meet the unique needs and preferences of every student. By leveraging data-driven insights, educators can create dynamic, engaging, and inclusive learning environments that foster student agency, mastery, and lifelong learning. However, realizing the full potential of personalized learning requires a concerted effort to address challenges related to data privacy, equity, teacher professional development, and ethical considerations. As we continue to harness the power of data analytics in education, we can unlock new possibilities for personalized learning and empower every student to thrive in the 21st century.

Data analytics offers the tools necessary to solve the problem of the one-size-fits-all model in education by enabling personalized learning paths. By leveraging student data effectively, schools can not only improve academic outcomes but also foster a more engaging and supportive learning environment.

Data analytics is transforming the education landscape by providing educators with insights into student performance, learning patterns, and instructional effectiveness. By utilizing various types of data, including assessment data, attendance and engagement data, behavioral data, LMS data, and socioeconomic data, educators can gain a comprehensive understanding of students' needs and tailor instruction accordingly. Moreover, predictive analytics offers the ability to anticipate student performance and identify at-risk students, enabling timely interventions.

The outcomes we analyzed and the findings we made for each one of the datasets in this paper lead us to several outcomes and recommendations that will probably help in future research. The analysis of the impact of parental education on student performance shows clearly that students with higher parental education tend to score higher on average, with a little more weight on maternal education. Thank makes sense, since mothers usually help their children with their studies, of the kids themselves take the example of behavior of their parents. The analysis about the impact of hours studied and attendance of the students on exam score showed that as the number of hours studied increases, the exam score should also increase, and similarly better attendance leads to higher exam scores. In both subjects, there are some outliers, and we came to an outcome that, some students who studied many hours and have high attendance but still had lower exam scores, indicating diminishing returns or other factors like study methods or stress etc. So as a recommendation for a research paper is to analyze several specific patterns of behaviors and facts as a group. The analysis of the impact of stress level on students' performance shows that students with a fabulous stress level have the best grades, although with a small scale of difference from the other cases. So, we can consider that the way of thinking of each student plays an important role here, by who rate their stress as "Bad" face challenges that severely impact their performance, while students who report "Fabulous" might have found a way to thrive under pressure. So, it can be answered by research that separates these factors. The analysis of the impact of the students' age on the final grades clearly shows that at the age of 16 the students have the best scores, with great difference from other ages. It is also obvious the lowest performance at the age of 15. As a recommendation, we suggest that there can be research that investigates the curriculum and support systems for 15-year-olds, to identify potential reasons for their lower average grades. Also, it can be considered to provide additional resources or programs for students aged 17 and 18 to enhance their performance as they prepare for their next academic or career steps. A final recommendation about a possible investigation is to continue to monitor performance trends across age groups to identify any shifts in student outcomes and adapt educational strategies accordingly. About the impact of student gender on the college mark, as many research and findings shows, females have highest college marks than men. Maybe it can be a biological research that tests females' brain of act about lessons and try to do a presentation in males or test males' brain and find a way of lesson that fits in their brain. About the impact of the extracurricular activities on the exam score there seems to be a small difference about exam score, so these outcomes indicate that students who participate in extracurricular activities generally benefit from the many opportunities afforded them. Of course, the small score difference may be due to a situation where students are overscheduled in too many activities and find that the benefits of participating in out-of-school activities may decrease. So, there can be a research that suggests the proper amount of time that fits a child's daily routine. Next, the outcome of the impact of sleep hours on the exam score showed no effect on the average exam score. For this area, there are tons of things that may influence the sleep. It is mostly organic, and it is a fact that the correct sleep hours differ from age to age. Also, based of phycology, heredity, and external factors, sleep hours may differ from child to child. About the impact of social media spent time it is revealed that students who spend fewer hours (5hours and less) on social media had higher performance mean score than those that spend more time. This means that time spent on a social network by the students has a significant influence on their academic performance in science. Based on the findings, it was recommended among others, that teachers should leverage on these social media to be giving students assignment and instructions to engage them meaningfully on the usage of the social media [15]. Finally, the impact of willingness to pursue a career based on their degree on students' performance analysis showed that willingness clearly affects the students' performance. Exactly as we see happening in the work sector. Of course, this happens nowadays because not everyone has the choice to do what they want as a profession, and of course children, regardless of age, are not sure that they have found what profession they want to pursue. So, it is good for teachers to constantly find ways to make the lesson interesting and interactive in a standard way so that they can learn each field correctly and choose more objectively.

As an observation, we need to track these averages over multiple years to see if these patterns hold or change, offering deeper insights into educational effectiveness.

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