Project Report on

INFLUENCE OF AI ASSISTANCE ANALYSIS IN STUDENT'S LEARNING

In partial fulfilment for the award

Of

Professional Certification in Data Analysis and Visualization

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Submitted By

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Tools & Technologies Used:

Python, R Programming, Tableau

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ABSTRACT

This project, titled "Influence of AI Assistance in Student Learning," explores the patterns and impacts of AI assistant usage among students. It focuses on key factors such as student level, discipline, session length, total prompts, task type, AI assistance level, final outcome, repeated usage, and satisfaction ratings. With the increasing integration of AI tools in education, understanding their influence on student learning and well-being is crucial. To carry out this analysis, a combination of tools was used. Python was applied for data cleaning and exploratory data analysis to uncover trends in the dataset. R programming was used to perform statistical analysis to check the significance of observed patterns. Tableau was used to build interactive dashboards that visually present the results for easier understanding.

The findings show that undergraduate students are the primary users of AI assistance. The analysis also indicates a significant relationship between AI assistance level and satisfaction, and that different task types lead to varying levels of student satisfaction. These insights can help educational institutions and AI tool developers create better AI assistance policies and support systems tailored to student needs. This project demonstrates how combining Python, R, and Tableau can provide a complete and practical view of AI assistance usage in student life.

INTRODUCTION

The integration of AI assistance into educational settings has become a notable change in modern learning environments. While AI tools offer benefits such as quick information retrieval and task automation, they also introduce new aspects that need to be understood—particularly in terms of student engagement, learning outcomes, and satisfaction. Many students are incorporating AI into their academic routines, leading to a need to understand how these tools impact their learning processes and overall academic experience.

This project, titled "Influence of AI Assistance in Student Learning," aims to explore how AI assistance influences key factors such as student level, discipline, and task type. It focuses on analysing patterns in AI usage among students using a comprehensive dataset. A combination of tools was used for the analysis: Python for data cleaning and exploratory analysis, R programming for statistical analysis, and Tableau for creating interactive dashboards. Together, these tools provide both detailed insights and easy-to-understand visuals for stakeholders like educators and policy makers. By integrating Python, R, and Tableau, this project offers a well-rounded, data-driven understanding of AI assistance usage in student life. The findings aim to support educational institutions in designing better policies and providing more effective guidance for students using AI tools.

LITERATURE REVIEW

- **Holmes, Bialik & Fadel (2019)**
  Artificial Intelligence in Education: Promises and Implications for Teaching and Learning further emphasize that task clarity and goal orientation enhance AI's impact. When assignments have defined structure, AI can offer precise guidance and actionable support, leading to higher student satisfaction
- **Generative AI in Programming Education (2025)**
  A study in *International Journal of Artificial Intelligence in Education* explored student perceptions and experiences using ChatGPT during coding exercises. It found that students who actively worked with GenAI tools reported higher usefulness, creative problem-solving ability, and willingness to continue using them in future work. This parallels your project's finding that coding tasks saw the highest satisfaction and reuse intent
- **AI-Assisted Pair Programming and Student Motivation (2025)**
  Research published in the *International Journal of STEM Education* compared AI-assisted pair programming versus traditional methods. Students using AI partners experienced less anxiety, improved motivation, and enhanced performance—especially when AI feedback was presented effectively. This supports your finding that AI assistance depth and prompt engagement positively impact satisfaction.
- **How AI Chatbots Shape Student Attitudes (2023)**
  A systematic review in *International Journal of Educational Technology in Higher Education* found that students generally view AI chatbots such as ChatGPT positively, particularly when these tools are used to clarify concepts and generate ideas. It also highlighted concerns around accuracy and the importance of background knowledge—aligned with your insight that research tasks rank lowest in satisfaction and reuse.
- **Real-World AI Report Logs Reveal Student Dependence (2025)**
  An investigative article by *The Guardian* examined 18 months of student personal advice, raising concerns over passivity and superficial thinking. It echoes your findings around the risk of low AI assistance or over-reliance leading to dissatisfaction or abandonment.
- **Ethical challenges & AI Education(2023)**
  A scoping review on practical and ethical challenges of large language models in education identified transparency, bias, data privacy, and trust as major barriers to adoption. These challenges underscore the need for clear assistance levels and robust systems—reinforcing your success findings tied to high AI assistance and student trust in structured tasks.

- **Impact of AI Tools on Study Habits and GPA (2024)**
  A mixed-methods study found that using AI tools helped students manage time, improve study habits, and achieve better academic performance. The report noted potential over-reliance as a downside. This supports your insight that deeper prompt usage and session strategy matter more than mere access or quantity.
- **Machine Learning and Dashboards for Education (2025)**
  A literature review of AI tutoring systems highlights emerging trends in adaptive platforms and real-time feedback dashboards. These tools personalize learning and support educators—mirroring your recommendation to build interactive systems like Streamlit or Dash for real-time monitoring.

RESEARCH GAP

Many past studies have looked at how AI affects student learning, but most focus on specific AI applications or limited aspects of student interaction. Some studies are based on small groups or only use qualitative methods without deeper quantitative analysis. Also, very few studies use multiple tools together to explore and explain the data clearly.

This project fills that gap by using Python for data analysis, R for statistical testing, and Tableau for creating visual dashboards. It gives a complete and practical view of how AI assistance impacts various aspects of student life, from academic disciplines to satisfaction and outcomes.

DATA COLLECTION & PRE-PROCESSING

Data Source and Collection Methods

The dataset used in this project, ai_assistant_usage_student_life.csv, was provided from **Kaggle**. It contains information about AI assistant usage sessions, including details such as :

- **SessionID** Unique session identifier
- **StudentLevel** Academic level (e.g., High School, Undergraduate, Graduate)
- **Discipline** Student’s field of study (e.g., CS, Psychology, etc.)
- **SessionDate** Date of the session
- **SessionLengthMin** Length of AI interaction in minutes
- **TotalPrompts** Number of prompts/messages used

- **TaskType** Nature of the task (e.g., Coding, Writing, Research)
- **AI_AssistanceLevel** 1–5 scale on how helpful the AI was perceived to be
- **FinalOutcome** What the student achieved (e.g., Assignment Completed, Idea Drafted, etc.)
- **UsedAgain** Whether the student returned to use the assistant again
- **SatisfactionRating** 1–5 rating of overall satisfaction with the session

Data Quality Assessment and Cleaning Procedures

Initial inspection of the dataset was done using Python with the help of the pandas ,matplotlib and numpy libraries. The following steps were taken:

- **Missing values:** The dataset was meticulously scanned for any instances of missing values. While the initial df.info() output indicated no null values.
- **Duplicate entries:** The dataset was scanned for duplicate rows using the .duplicated() method.
- **Data Types:** Ensured each column had the correct type for further processing (e.g., numerical ratings as float, categorical as objects/factors).
- **SessionID handling:** The original SessionID column was dropped, and a new SessionID was recreated based on the DataFrame index to ensure unique identifiers.
- **Detecting Outliers:** Outliers in numerical columns such as SessionID, SessionLengthMin, TotalPrompts, AI_AssistanceLevel and SatisfactionRating were identified using box plots to detect unusually high or low values.

Feature Engineering and Selection Techniques

For specific analyses and visualizations, the following steps were taken:

- Relevant columns were selected for various analyses, including

  StudentLevel, Discipline, SessionLengthMin, TotalPrompts, TaskType, AI_AssistanceLevel, FinalOutcome, UsedAgain, and SatisfactionRating.

Columns Selected for Analysis

- **Average Session Length by Task Type:** This shows how long students typically spend using AI for different tasks. (e.g., Brainstorming takes the longest).
- **Average Prompts by Discipline:** This indicates which academic fields use the AI most interactively. (e.g., Engineering students use more prompts).

- **Average AI Assistance Level by Task Type:** This reveals which tasks are perceived to need more complex help from the AI. (e.g., Coding and Homework Help need higher assistance).
- **Average Satisfaction: Used Again vs. Not:** This compares satisfaction levels for students who reuse the AI versus those who don't. (Surprisingly, those who didn't reuse had slightly higher satisfaction).
- **Most Common Task Type per Discipline:** This identifies the primary use of AI across all study areas. (e.g., Writing is the most common task for all disciplines).
- **Average Prompts for Different Final Outcomes:** This checks if more interaction leads to better results. (e.g., Students who "Gave Up" used the most prompts, suggesting struggles).
- **Percentage of Sessions by Student Level:** This shows which student groups use AI the most. (e.g., Undergraduates are the heaviest users).
- **Most Frequently Used AI Assistance Level:** This points to the preferred level of help students get from the AI. (e.g., Moderate to high assistance levels are most common).
- **Most Common Final Outcome:** This reveals the primary goal students achieve with AI. (e.g., "Assignment Completed" is the most frequent outcome).
- **Average Prompts per Task Type:** This details how many interactions different tasks typically require. (e.g., Brainstorming needs the most prompts, showing its iterative nature).
- **Relationship between TaskType and UsedAgain:** This explains which tasks are most likely to make students come back and use the AI again. (e.g., Coding leads to the highest re-usage, Research the lowest).

METHODOLOGY

This project follows a multi-tool analytical approach combining Python, R programming, and Tableau to analyse the impact of AI assistance usage on student learning and satisfaction. The methodology is designed to provide a comprehensive view of the dataset, validate the findings with statistical tests, and present the insights in a user-friendly manner.

Tools and Technologies Used

- **Python:** Used for data cleaning, transformation, and exploratory analysis. Key libraries like pandas, numpy, matplotlib and seaborn enabled efficient data handling, visualization, and the identification of patterns.
- **R programming:** Utilized for statistical hypothesis testing to validate the patterns discovered during EDA. Key packages and functions such as t.test(), ANOVA(), chi-square.test(), z.test(), and (F-test) helped in performing parametric and non-parametric tests.
- **Tableau:** Used for building interactive dashboards and data visualization, presenting the findings to non-technical stakeholders in a clear and intuitive format.

Exploratory Data Analysis – Python

With the data cleaned, exploratory analysis was conducted to identify trends and patterns using pandas, matplotlib, seaborn, and numpy. This step allowed for the visualization of key relationships between variables, which guided the choice of statistical tests in R.

- **Visualizations:**
    - **Pie Charts:** Used to show the distribution of categorical variables like StudentLevel.
    - **Histograms and Box Plots:** To visualize the distribution of numerical variables such as SessionLengthMin and TotalPrompts.
    - **Bar Plots:** Used to compare different groups, e.g., average SatisfactionRating by TaskType.
    - **Scatter Plots:** To explore relationships between two numerical variables, like SessionLengthMin and TotalPrompts.
    - **Heatmaps:** For correlation analysis among numerical features.
- **Groupby and Value Counts:**
    - Used value_counts() to understand the frequency of categories in columns like StudentLevel and TaskType.

    - Used groupby() to aggregate and analyse means, counts, and distributions based on different features, such as average SatisfactionRating by TaskType.

Statistical Testing (R Programming)

The exploratory insights from Python were validated using statistical hypothesis testing in R. Several tests were employed to confirm whether the observed patterns were statistically significant.

- **T-test:** Used to compare the mean SatisfactionRating between groups (e.g., UsedAgain as True/False).
- **Z-test:** Applied to compare the mean SessionLengthMin against a hypothesized population mean.
- **F-test:** Used to test for equality of variances, such as comparing the TotalPrompts variance across different disciplines.
- **ANOVA:** Conducted to compare the means of SatisfactionRating across multiple TaskType groups.
- **Chi-square Test:** Used to test the independence between two categorical variables, such as TaskType and UsedAgain.

Data Visualization and Dashboarding – Tableau

After completing the data preparation and analysis in Python, Tableau was used to create an interactive and user-friendly dashboard. Tableau was selected for its ability to present complex data in a visual format, making it easier for stakeholders to interpret and act on the insights.

- **Interactive Filters:** Filters allow users to explore different subsets of the data based on various dimensions like StudentLevel, Discipline, and TaskType.
- **Simple Layout and Clear Visuals:** The dashboard is designed with a clean layout, using appropriate chart types, colour coding, and labels to highlight key findings, ensuring that users can easily identify trends and patterns.

RESULTS AND ANALYSIS

This section presents the key findings of the project, focusing on how AI assistance usage varies among students and its impact on their outcomes.

Python - Based Results

- The majority of AI assistant users are Undergraduate students (59.78%), followed by High School (20.27%) and Graduate students (19.95%).
- Students rated their AI-assisted coding sessions at **3.46/5**, the highest among all task types.
- AI-assisted research tasks had an average satisfaction of **3.34/5**, indicating limited effectiveness for deep academic research.
- **31% of all sessions** were writing-related, showing that students most frequently use AI for generating written content.
- Students who received the **maximum level of AI help (Level 5)** gave an average satisfaction rating of **4.67/5**.
- Students issuing **8+ prompts** had significantly higher satisfaction (≈ **4.2/5**) than those who used fewer prompts.
- These students reported average satisfaction scores of **above 3.44**, showing strong alignment with AI support.
- Despite high prompt counts, CS students gave a lower satisfaction rating (**3.42**) than Biology or History students.
- **47.7%** of sessions ended in successful task completion, proving AI's usefulness in academic productivity.
- **74.2%** of students who used AI for coding said they would reuse it, indicating high trust in AI for programming.
- Only **64.3%** of students doing research tasks said they would reuse AI, suggesting a need for improvement in this area.
- These sessions had the **highest satisfaction (3.43)**, making them the ideal duration for productive AI use.
- A small percentage of sessions resulted in abandonment, showing that AI tools are generally supportive and user-friendly.

R-Based Statistical Results

1. **T-test Result:**
   There was **no statistically significant difference** in the average satisfaction ratings between students who indicated they would use AI again and those who would not (**$p = 0.3461 > 0.05$**). This suggests that overall satisfaction is relatively consistent regardless of future reuse intent.

2. **Z-test Result:**
   The average session length with AI tools (**19.85 minutes**) is **significantly lower** than the expected benchmark of 25 minutes (**$p < 0.001$**). This implies that students generally prefer shorter AI interactions for academic tasks.
3. **F-test Result:**
   The variance in the number of AI prompts used by **Computer Science vs. Psychology students** is **statistically different** (**$p = 0.019 < 0.05$**). This indicates that engagement with AI (as measured by prompt count) varies more in one discipline than the other, likely due to differing task types or familiarity with AI.

4. **ANOVA Result:**
   The analysis found **no statistically significant difference** in satisfaction scores across different task types like Writing, Coding, and Research (**$p = 0.384 > 0.05$**). This suggests students rated AI similarly across academic tasks.
5. **Chi-Square Test Result:**
   There is a **statistically significant relationship** between the type of task students perform and their willingness to reuse AI tools in the future (**$p < 0.001$**). This shows that certain academic tasks may lead to higher trust or perceived usefulness of AI.

Tableau- Based Results

- Students doing coding tasks rated their experience higher than any other task type.
- Only **70.64%** of students who used AI and intend to reuse it, suggesting AI tools need improvement for in-depth academic tasks.
- Medium-lenth sessions (10–30 minutes) are the sweet spot for satisfaction These sessions had the highest average satisfaction (3.43/5), outperforming short and long sessions.
- Maximum AI assistance directly leads to excellent satisfaction At AI Assistance Level 5, students reported average satisfaction of 4.67/5, the highest across all levels.
- Students who used more than 8 prompts per session had the best outcomes More interactive sessions (8+ prompts) correlated with satisfaction scores above 4.2, showing that depth of engagement matters.
- Biology and History students are highly satisfied despite moderate AI use These students rated AI above 3.44/5, proving that targeted use can be more effective than frequent use.

- Nearly half (47.7%) of AI sessions end with a completed assignment This confirms that AI is not just experimental — it leads to real academic outcomes.
- Low AI assistance levels result in poor user experience Students receiving minimal help (Level 1–2) reported satisfaction scores below 2.0, emphasizing the need for meaningful AI responses.

CONCLUSION

This project provided a comprehensive analysis of AI assistance usage trends in student learning. Through detailed data exploration, statistical testing, and visual storytelling, the study identified meaningful relationships between AI usage patterns, student characteristics, and outcomes.

The findings show that AI assistance is being adopted by students across different levels and disciplines, with undergraduates being the most frequent users. There is a clear link between the level of AI assistance provided and student satisfaction. Furthermore, the type of task significantly influences both student satisfaction and the likelihood of them using AI tools again.

Overall, this project highlights the importance of understanding the nuances of AI integration in education to maximize its benefits for student learning and well-being. By combining Python, R, and Tableau, the analysis not only reveals key insights but also demonstrates a scalable approach that educational institutions and AI developers can adopt to monitor and improve the effectiveness of AI assistance in academic settings.

FUTURE WORKS

- **Implement predictive modelling** to identify factors that lead to higher satisfaction or academic success using machine learning techniques.
- **Integrate real-time data** from AI assistant platforms for continuous monitoring of usage patterns and immediate feedback.
- **Develop an interactive web dashboard** using tools like Stream lit or Dash for real-time visualization and decision-making by educators and administrators.
- **Expand the dataset** by including more demographic information (e.g., academic performance, prior AI experience) for a broader analysis.
- **Explore advanced analytics** like natural language processing (NLP) on prompt content to uncover deeper insights into student queries and needs.
- **Automate reporting** using scheduled scripts to generate weekly or monthly AI usage reports for educational institutions.

REFERENCES

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SUPPORTING FILES

Python:

Exploring Student Engagement with AI Learning Tools (2024–2025)

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

```
df=pd.read_csv(r"C:\Users\HP\Downloads\ai_assistant_usage_student_life.csv")
df
```

```
df.drop("SessionID",axis=1,inplace=True)
df
```

```
df=df.reset_index().rename(columns={'index': 'SessionID'})
```

```
df.head()
```

```
df.tail()
```

```
df.shape
```

```
df.size
```

```
df.columns
```

```
df.dtypes
```

```
df.info
```

```
df.describe(include='all').T
```

```
df.duplicated().sum()
```

```
df.isnull().sum()
```

```
df.nunique()
```

```
#unique values of each features
for i in df.columns:
    print(i)
    print(df[i].unique())
    print('-'*50)
    print('\n')
```

Outlier Detecting

```
#number columns
int_col=df.select_dtypes('number')
int_col
```

```
for i in int_col:
    sns.boxplot(df[i])
    plt.title(i)
    plt.show()
```

```
int_col.columns
```

```
#Outlier handling
for x in ['SessionID', 'SessionLengthMin', 'TotalPrompts', 'AI_AssistanceLevel']:
    q1=df[x].quantile(0.25)
    q3=df[x].quantile(0.75)
    iqr=q3-q1
    lower=q1-1.5*iqr
    upper=q3+1.5*iqr
    df[x]=np.clip(df[x],upper,lower)
```

```
for i in int_col:
    sns.boxplot(df[i])
    plt.title(i)
    plt.show()
```

Analysis

1 What is the average session length for each task type?

```
df.groupby('TaskType')['SessionLengthMin'].mean().sort_values(ascending=False)
```

2 Which discipline uses the highest average number of prompts?

```
df.groupby('Discipline')['TotalPrompts'].mean().sort_values(ascending=False)
```

3 What is the average AI Assistance Level per task type?

```
df.groupby('TaskType')['AI_AssistanceLevel'].mean().sort_values(ascending=True)
```

4 What is the average satisfaction rating for students who would use AI again vs not?

```
df.groupby('UsedAgain')['SatisfactionRating'].mean()
```

5 What's the most common task type per discipline?

```
df.groupby('Discipline')['TaskType'].agg(lambda x: x.mode()[0])
```

6 What is the average number of prompts for completed vs not completed outcomes?

```
df.groupby('FinalOutcome')['TotalPrompts'].mean().sort_values(ascending=False)
```

7 What percentage of sessions were from each student level?

```
df['StudentLevel'].value_counts(normalize=True) * 100
```

8 Which AI assistance level is used most frequently?

```
df['AI_AssistanceLevel'].value_counts().sort_values(ascending=False)
```

9 What is the most common final outcome across all sessions?

```
df['FinalOutcome'].value_counts()
```

10 What is the average number of prompts per task type?

```
df.groupby('TaskType')['TotalPrompts'].mean().sort_values(ascending=False)
```

11 What is the relationship between the TaskType and whether a student UsedAgain the AI assistant?

```
pd.crosstab(df['TaskType'],df['UsedAgain'],normalize=True)
```

Visualization

What is the distribution of student levels in AI assistant usage?

```
plt.figure(figsize=(8,5))
sns.countplot(x='StudentLevel',data=df,palette='pastel')
plt.title('Distribution of Student Levels')
plt.xlabel('Student Level')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```

Are students more satisfied with more advanced AI help?

```
ai_satisfaction = df.groupby('AI_AssistanceLevel')['SatisfactionRating'].mean()

plt.figure(figsize=(8,4))
sns.lineplot(x=ai_satisfaction.index, y=ai_satisfaction.values, marker='o', color='green')
plt.title('Satisfaction by AI Assistance Level')
plt.xlabel('AI Assistance Level')
plt.ylabel('Avg. Satisfaction Rating')
plt.grid(True)
plt.tight_layout()
plt.show()
```

What are the most common final outcomes of AI-assisted student sessions?

```
outcome_counts = df['FinalOutcome'].value_counts()

plt.figure(figsize=(6,6))
plt.pie(outcome_counts, labels=outcome_counts.index, autopct='%1.1f%%', startangle=140, wedgeprops={'width':0.4})
plt.title('Final Outcome Distribution')
plt.tight_layout()
plt.show()
```

Is higher AI Assistance Level always linked to higher prompt counts?

```
plt.figure(figsize=(8,5))
sns.boxplot(x='AI_AssistanceLevel', y='TotalPrompts', data=df, palette='coolwarm')
plt.title('Prompt Count by AI Assistance Level')
plt.tight_layout()
plt.show()
```

How do numeric features correlate with each other?

```
plt.figure(figsize=(8, 6))
numeric_cols = df.select_dtypes(include=['float64', 'int64']).columns
correlation_matrix = df[numeric_cols].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap of Numeric Features')
plt.tight_layout()
plt.show()
```

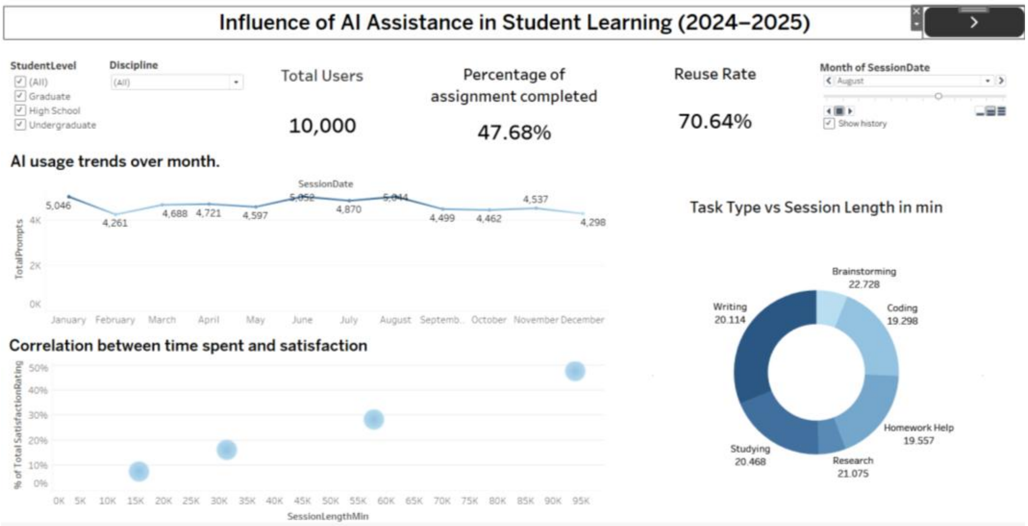
R Programming:

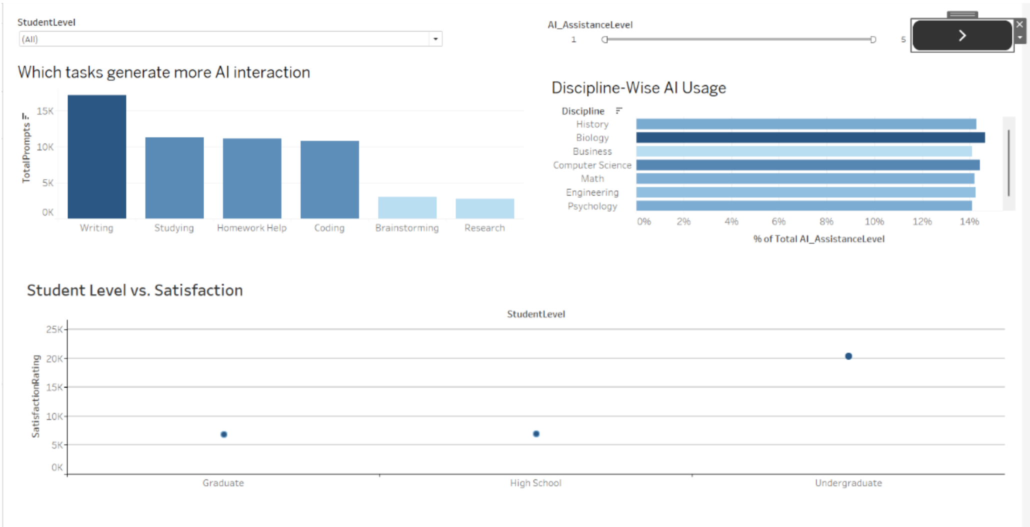
```
install.packages("dplyr")
library("dplyr")

df<-read.csv("C:\\Users\\HP\\Downloads\\ai_assistant_usage_student_life.csv")
View(df)

summary(df)
head(df)
str(df)

# T-test
# Does SatisfactionRating differ based on whether students would Use AI Again?
# Convert 'UsedAgain' to factor
df$UsedAgain <- as.factor(df$UsedAgain)

#run the t-test

t_result1 <- t.test(SatisfactionRating ~ UsedAgain, data = df)
print(t_result1)

# Interpretation

if (t_result1$p.value < 0.05) {
  print("The difference is statistically significant (p < 0.05)\n")
} else {
  print("The difference is NOT statistically significant (p = 0.05)\n")
}

#Z-test

install.packages("BSDA")
library(BSDA)

z_result <- z.test(df$SessionLengthMin, mu = 25, sigma.x = 10)
print(z_result)
```

```
if (z_result$p.value < 0.05) {
  print("The difference is statistically significant (p < 0.05)\n")
} else {
  print("The difference is NOT statistically significant (p = 0.05)\n")
}

# F-test

# Subset data for Computer Science and Psychology
cs_prompts <- subset(df, Discipline == "Computer Science")$TotalPrompts
psy_prompts <- subset(df, Discipline == "Psychology")$TotalPrompts

# Perform F-test to compare variances
f_result <- var.test(cs_prompts, psy_prompts)

# Print result
print(f_result)

if (f_result$p.value < 0.05) {
  print("The difference is statistically significant (p < 0.05)\n")
} else {
  print("The difference is NOT statistically significant (p = 0.05)\n")
}
```

```
#Anova Test
# Do different Task Types lead to different levels of student Satisfaction Rating?

# Perform ANOVA: compare Satisfaction Rating across Task Type
anova_result <- aov(SatisfactionRating ~ TaskType, data = df)

# Summary of ANOVA
summary(anova_result)

anova_summary <- summary(anova_result)
p_val <- anova_summary[[1]]["Pr(>F)"][1]

# Now make the decision
  if (t_result1$p.value < 0.05) {
    print("The difference is statistically significant (p < 0.05)\n")
  } else {
    print("The difference is NOT statistically significant (p = 0.05)\n")
  }

# Chi Square Test

# Create contingency table
contingency_table <- table(df$TaskType, df$UsedAgain)

# View the table
print(contingency_table)

# Perform Chi-Square Test
chi_result <- chisq.test(contingency_table)

# Print result
print(chi_result)

# Interpretation
if (chi_result$p.value < 0.05) {
    print("The difference is statistically significant (p < 0.05)\n")
  } else {
    print("The difference is NOT statistically significant (p = 0.05)\n")
  }
```

Tableau:


Influence of AI Assistance in Student Learning (2024–2025)
StudentLevel
(All)
Graduate
High School
Undergraduate
Discipline
(All)
Total Users
10,000
Percentage of assignment completed
47.68%
Reuse Rate
70.64%
Month of SessionDate
August
Show history
AI usage trends over month.
SessionDate
TotalPrompts
January
February
March
April
May
June
July
August
Septemb..
October
November
December
Correlation between time spent and satisfaction
% of Total SatisfactionRating
SessionLengthMin
Task Type vs Session Length in min
Brainstorming 22.728
Coding 19.298
Homework Help 19.557
Research 21.075
Studying 20.468
Writing 20.114


StudentLevel
(All)
AI_AssistanceLevel
Which tasks generate more AI interaction
TotalPrompts
Writing
Studying
Homework Help
Coding
Brainstorming
Research
Discipline-Wise AI Usage
Discipline
History
Biology
Business
Computer Science
Math
Engineering
Psychology
% of Total AI_AssistanceLevel
Student Level vs. Satisfaction
StudentLevel
SatisfactionRating
Graduate
High School
Undergraduate