02_eda_streamlined_for_modeling

September 2, 2025

1 Streamlined EDA for Student Performance Analysis

Project Objectives: 1. **K-means clustering** using 6 behavioral features: studytime, absences, goout, freetime, famsup, schoolsup 2. **Binary classification** for pass/fail prediction

This notebook contains only the essential visualizations that directly support these modeling objectives.

[44]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from scipy.stats import chi2_contingency
import warnings

warnings.filterwarnings("ignore")

# Set professional styling
sns.set_style("whitegrid")
plt.rcParams.update(
    {
        "figure.figsize": (10, 6),
        "font.size": 11,
        "axes.titlesize": 14,
        "axes.labelsize": 12,
        "axes.grid": True,
        "grid.alpha": 0.3,
        "axes.spines.top": False,
        "axes.spines.right": False,
    }
)

# Load data
df = pd.read_pickle(r"../data/processed/cleaned_dataset.pkl")

# Create numeric version for correlations
df_numeric = df.copy()
```

```python
for col in df_numeric.columns:
    if df_numeric[col].dtype == "category":
        df_numeric[col] = df_numeric[col].cat.codes
    elif df_numeric[col].dtype == "bool":
        df_numeric[col] = df_numeric[col].astype(int)

print("Data loaded successfully!")
print(f"Dataset shape: {df.shape}")
```

```
Data loaded successfully!
Dataset shape: (649, 34)
```

[45]:
```python
#   CONSISTENT STYLE CONFIGURATION
# Set up professional, consistent styling for all plots

# Set seaborn style and palette
sns.set_style("whitegrid")
sns.set_palette("viridis")

# Set matplotlib parameters for consistency
plt.rcParams.update(
    {
        "figure.figsize": (10, 6),  # Default figure size
        "font.size": 11,  # Base font size
        "axes.titlesize": 14,  # Title font size
        "axes.labelsize": 12,  # Axis label font size
        "xtick.labelsize": 10,  # X-tick label size
        "ytick.labelsize": 10,  # Y-tick label size
        "legend.fontsize": 10,  # Legend font size
        "axes.grid": True,  # Enable grid
        "grid.alpha": 0.3,  # Grid transparency
        "lines.linewidth": 2,  # Line width
        "axes.spines.top": False,  # Remove top spine
        "axes.spines.right": False,  # Remove right spine
    }
)

# Color constants for consistent theming
COLORS = {
    "primary": "#3691d2",  # Blue
    "secondary": "#ff7f0e",  # Orange
    "success": "#2ca02c",  # Green
    "danger": "#d62728",  # Red
    "warning": "#ff7f0e",  # Orange
    "threshold": "#d62728",  # Red for pass/fail lines
    "data_leakage": "#ff7f0e",  # Orange for G1/G2 warnings
}
```

```python
print(" Professional styling configured!")
```

```
 Professional styling configured!
```

1.1 Descriptive Statistics

[46]:
```python
# Descriptive statistics for numeric variables
df.describe()
```

[46]:
```
              age    failures    absences          G1          G2          G3  \
count  649.000000  649.000000  649.000000  649.000000  649.000000  649.000000
mean    16.744222    0.221880    3.659476   11.399076   11.570108   11.906009
std      1.218138    0.593235    4.640759    2.745265    2.913639    3.230656
min     15.000000    0.000000    0.000000    0.000000    0.000000    0.000000
25%     16.000000    0.000000    0.000000   10.000000   10.000000   10.000000
50%     17.000000    0.000000    2.000000   11.000000   11.000000   12.000000
75%     18.000000    0.000000    6.000000   13.000000   13.000000   14.000000
max     22.000000    3.000000   32.000000   19.000000   19.000000   19.000000

        pass_fail
count  649.000000
mean     0.845917
std      0.361307
min      0.000000
25%      1.000000
50%      1.000000
75%      1.000000
max      1.000000
```

[47]:
```python
df.describe(include="category")
```

[47]:
```
       school  sex address famsize Pstatus  Medu  Fedu   Mjob   Fjob  reason  \
count     649  649     649     649     649   649   649    649    649     649
unique      2    2       2       2       2     5     5      5      5       4
top        GP    F       U     GT3       T     2     2  other  other  course
freq      423  383     452     457     569   186   209    258    367     285

       guardian traveltime  studytime famrel  freetime goout  Dalc  Walc  \
count       649        649        649    649       649   649   649   649
unique        3          4          4      5         5     5     5     5
top      mother          1          2      4         3     3     1     1
freq        455        366        305    317       251   205   451   247

        health
count      649
unique       5
top          5
```

```
freq        249
```

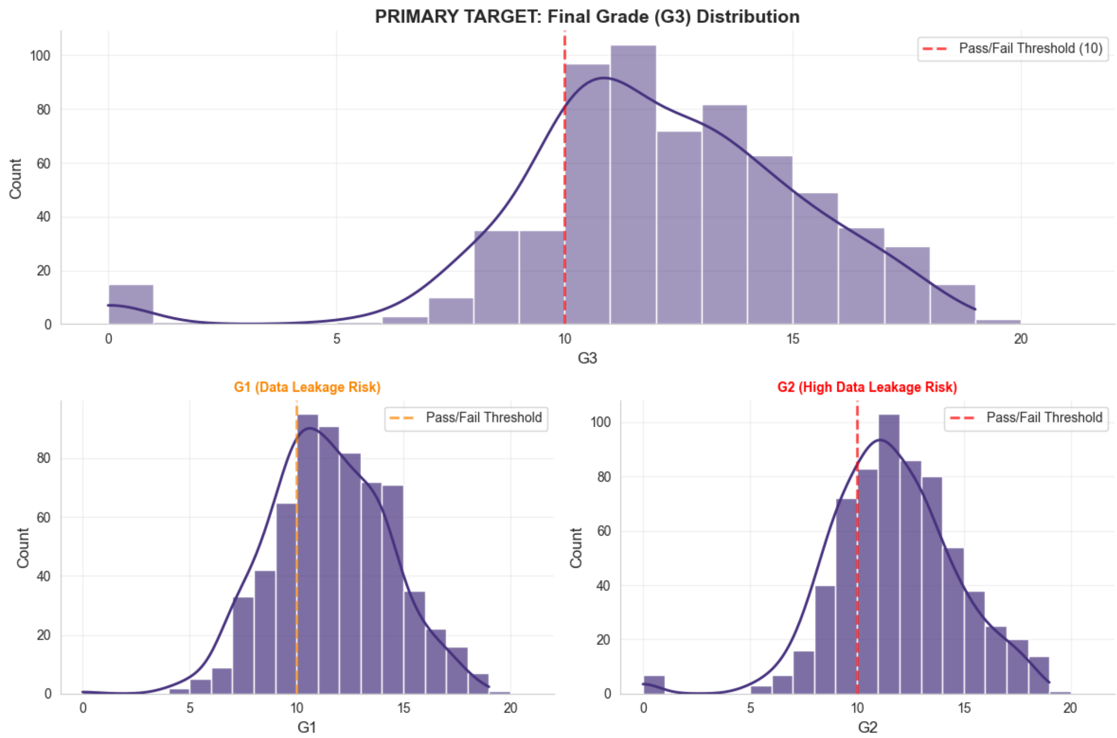
[48]:
```
df.describe(include="bool")
```

[48]:
```
       schoolsup famsup   paid activities nursery higher internet romantic
count        649    649    649        649     649    649      649      649
unique         2      2      2          2       2      2        2        2
top        False   True  False      False    True   True     True    False
freq         581    398    610        334     521    580      498      410
```

1.2 Target Variable Distribution

[62]:
```
# Primary focus: Target variable
plt.figure(figsize=(12, 8))
plt.subplot(2, 2, (1, 2))  # Span two columns for G3
sns.histplot(data=df, x="G3", bins=range(0, 22), kde=True)
# Add pass/fail threshold line with legend
plt.axvline(
    x=10,
    color="red",
    linestyle="--",
    linewidth=2,
    alpha=0.7,
    label="Pass/Fail Threshold (10)",
)
plt.title(
    "PRIMARY TARGET: Final Grade (G3) Distribution", fontsize=14,␣
  ↪fontweight="bold"
)
plt.legend()

# Context: Grade progression
plt.subplot(2, 2, 3)
sns.histplot(data=df, x="G1", bins=range(0, 22), kde=True, alpha=0.7)
plt.axvline(
    x=10,
    color="#fb8500",
    linestyle="--",
    linewidth=2,
    alpha=0.7,
    label="Pass/Fail Threshold",
)
plt.title("G1 (Data Leakage Risk)", fontsize=10, color="#fb8500",␣
  ↪fontweight="bold")
plt.legend()
```

```python
plt.subplot(2, 2, 4)
sns.histplot(data=df, x="G2", bins=range(0, 22), kde=True, alpha=0.7)
plt.axvline(
    x=10,
    color="red",
    linestyle="--",
    linewidth=2,
    alpha=0.7,
    label="Pass/Fail Threshold",
)
plt.title("G2 (High Data Leakage Risk)", fontsize=10, color="red",␣
 ↪fontweight="bold")
plt.legend()

plt.tight_layout()
plt.show()

# Statistical summary
pass_count = df["pass_fail"].sum()
fail_count = (df["pass_fail"] == 0).sum()
pass_rate = pass_count / len(df) * 100

print(f"Class Distribution Analysis:")
print(f"Pass (G3 >= 10): {pass_count} students ({pass_rate:.1f}%)")
print(f"Fail (G3 < 10): {fail_count} students ({100-pass_rate:.1f}%)")
print(f"\nClass imbalance detected - this affects binary classification␣
 ↪performance.")
```



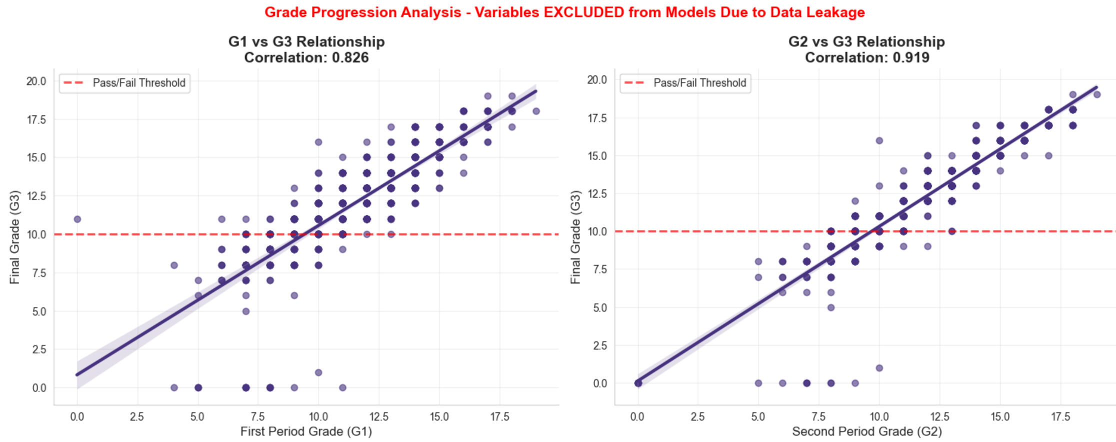

```
Class Distribution Analysis:
Pass (G3 >= 10): 549 students (84.6%)
Fail (G3 < 10): 100 students (15.4%)

Class imbalance detected - this affects binary classification performance.
```

1.3 Data Leakage Variables (G1, G2) - Excluded from Models

[51]:
```
# Visualization 2 & 3: Grade progression analysis - G1 vs G3 and G2 vs G3
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 6))
fig.suptitle(
    "Grade Progression Analysis - Variables EXCLUDED from Models Due to Data␣
↪Leakage",
    fontsize=14,
    fontweight="bold",
    color="red",
)

# G1 vs G3
sns.regplot(x="G1", y="G3", data=df, scatter_kws={"alpha": 0.6}, ax=ax1)
ax1.axhline(
    y=10,
```

```
    color="red",
    linestyle="--",
    linewidth=2,
    alpha=0.7,
    label="Pass/Fail Threshold",
)
g1_corr = df["G1"].corr(df["G3"])
ax1.set_title(f"G1 vs G3 Relationship\nCorrelation: {g1_corr:.3f}",␣
 ↪fontweight="bold")
ax1.set_xlabel("First Period Grade (G1)")
ax1.set_ylabel("Final Grade (G3)")
ax1.legend()

# G2 vs G3
sns.regplot(x="G2", y="G3", data=df, scatter_kws={"alpha": 0.6}, ax=ax2)
ax2.axhline(
    y=10,
    color="red",
    linestyle="--",
    linewidth=2,
    alpha=0.7,
    label="Pass/Fail Threshold",
)
g2_corr = df["G2"].corr(df["G3"])
ax2.set_title(f"G2 vs G3 Relationship\nCorrelation: {g2_corr:.3f}",␣
 ↪fontweight="bold")
ax2.set_xlabel("Second Period Grade (G2)")
ax2.set_ylabel("Final Grade (G3)")
ax2.legend()

plt.tight_layout()
plt.show()

print("DATA LEAKAGE WARNING:")
print(f"G1-G3 correlation: {g1_corr:.3f} - Very high correlation creates data␣
 ↪leakage")
print(
    f"G2-G3 correlation: {g2_corr:.3f} - Extremely high correlation creates␣
 ↪severe data leakage"
)
print(
    "\nThese variables will be EXCLUDED from predictive models to ensure␣
 ↪realistic performance estimates."
)
print(
    "For early intervention systems, we need to predict G3 from baseline␣
 ↪characteristics only."
```

```
)
```

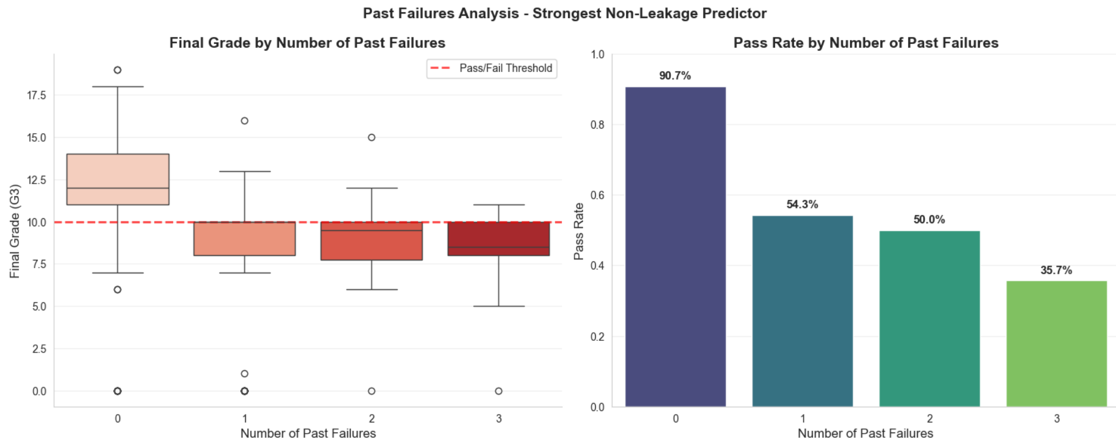



```
DATA LEAKAGE WARNING:
G1-G3 correlation: 0.826 - Very high correlation creates data leakage
G2-G3 correlation: 0.919 - Extremely high correlation creates severe data
leakage

These variables will be EXCLUDED from predictive models to ensure realistic
performance estimates.
For early intervention systems, we need to predict G3 from baseline
characteristics only.
```

1.4 Key Predictive Variables

[68]:
```
# Visualization 4: Past failures analysis - strongest predictor
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 6))
fig.suptitle(
    "Past Failures Analysis - Strongest Non-Leakage Predictor",
    fontsize=14,
    fontweight="bold",
)

# Failures vs G3 boxplot
sns.boxplot(x="failures", y="G3", data=df, ax=ax1, palette="Reds")
ax1.axhline(
    y=10,
    color="red",
    linestyle="--",
    linewidth=2,
    alpha=0.7,
```

```
    label="Pass/Fail Threshold",
)
ax1.set_title("Final Grade by Number of Past Failures", fontweight="bold")
ax1.set_xlabel("Number of Past Failures")
ax1.set_ylabel("Final Grade (G3)")
ax1.legend()

# Pass rate by failures
pass_rate_failures = df.groupby("failures")["pass_fail"].mean()
sns.barplot(
    x=pass_rate_failures.index, y=pass_rate_failures.values, ax=ax2,
 ↪palette="viridis"
)
ax2.set_title("Pass Rate by Number of Past Failures", fontweight="bold")
ax2.set_xlabel("Number of Past Failures")
ax2.set_ylabel("Pass Rate")
ax2.set_ylim(0, 1)

# Add percentage labels
for i, v in enumerate(pass_rate_failures.values):
    ax2.text(i, v + 0.02, f"{v:.1%}", ha="center", fontweight="bold")

plt.tight_layout()
plt.show()

failures_corr = df_numeric["failures"].corr(df_numeric["G3"])
print(f"Past failures correlation with G3: {failures_corr:.3f}")
print("Past failures show the strongest predictive power among non-leakage
 ↪variables.")
print("Critical for both clustering behavioral patterns and classification
 ↪models.")

# Critical failures impact analysis
print("\nPast Failures Impact Analysis:")
failures_stats = df.groupby("failures")["G3"].agg(["mean", "std", "count"]).
 ↪round(2)

print(failures_stats)
```

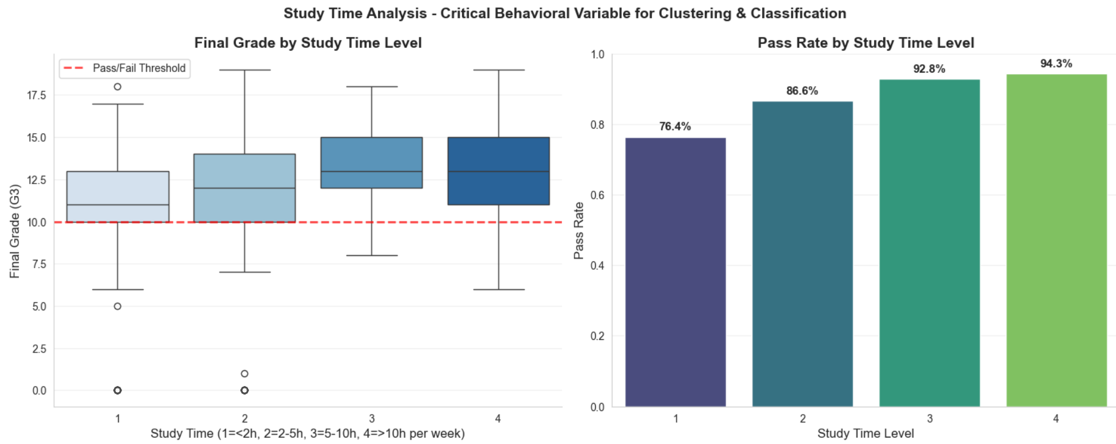



```
Past failures correlation with G3: -0.393
Past failures show the strongest predictive power among non-leakage variables.
Critical for both clustering behavioral patterns and classification models.

Past Failures Impact Analysis:
           mean   std  count
failures
0         12.51  2.83    549
1          8.64  3.44     70
2          8.81  3.21     16
3          8.07  2.79     14
```

[71]:

```
# Visualization 5: Study time analysis - key behavioral variable
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 6))
fig.suptitle(
    "Study Time Analysis - Critical Behavioral Variable for Clustering &␣
↪Classification",
    fontsize=14,
    fontweight="bold",
)

# Study time vs G3 boxplot
sns.boxplot(x="studytime", y="G3", data=df, ax=ax1, palette="Blues")
ax1.axhline(
    y=10,
    color="red",
    linestyle="--",
    linewidth=2,
    alpha=0.7,
    label="Pass/Fail Threshold",
)
ax1.set_title("Final Grade by Study Time Level", fontweight="bold")
```

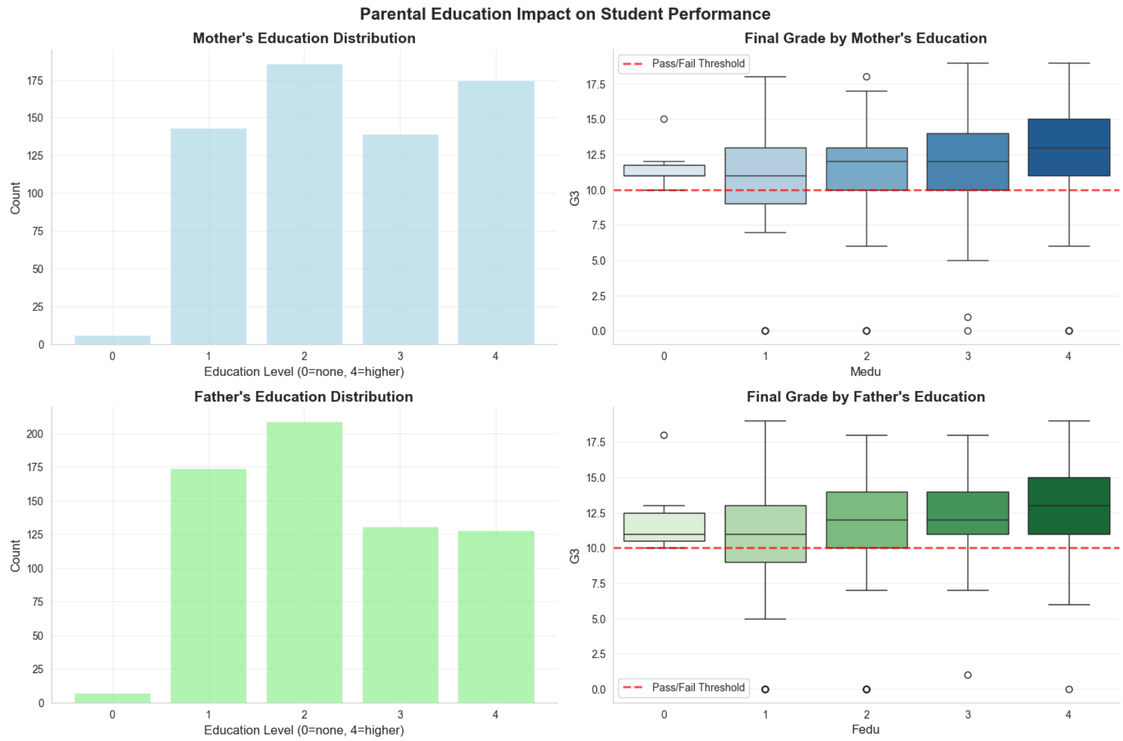
```
ax1.set_xlabel("Study Time (1=<2h, 2=2-5h, 3=5-10h, 4=>10h per week)")
ax1.set_ylabel("Final Grade (G3)")
ax1.legend()

# Study time pass rate
pass_rate_study = df.groupby("studytime")["pass_fail"].mean()
sns.barplot(
    x=pass_rate_study.index, y=pass_rate_study.values, ax=ax2, palette="viridis"
)
ax2.set_title("Pass Rate by Study Time Level", fontweight="bold")
ax2.set_xlabel("Study Time Level")
ax2.set_ylabel("Pass Rate")
ax2.set_ylim(0, 1)

# Add percentage labels
for i, v in enumerate(pass_rate_study.values):
    ax2.text(i, v + 0.02, f"{v:.1%}", ha="center", fontweight="bold")

plt.tight_layout()
plt.show()

studytime_corr = df_numeric["studytime"].corr(df_numeric["G3"])
print(f"Study time correlation with G3: {studytime_corr:.3f}")
print(
    "Study time shows clear progressive improvement in both median grades and␣
 ↪pass rates."
)
print("Essential variable for behavioral clustering and predictive␣
 ↪classification.")

# Statistical summaries
print("\n  Study Time Impact:")
studytime_stats = df.groupby("studytime")["G3"].agg(["mean", "std", "count"]).
 ↪round(2)

print(studytime_stats)
```




```
Study time correlation with G3: 0.250
Study time shows clear progressive improvement in both median grades and pass
rates.
Essential variable for behavioral clustering and predictive classification.

 Study Time Impact:
           mean   std  count
studytime
1         10.84  3.22    212
2         12.09  3.24    305
3         13.23  2.50     97
4         13.06  3.04     35
```

[63]:
```
# Parental Education Analysis (Medu, Fedu)
fig, axes = plt.subplots(2, 2, figsize=(15, 10))
fig.suptitle(
    "Parental Education Impact on Student Performance", fontsize=16,␣
 ↪fontweight="bold"
)

# Mother's education distribution
medu_counts = df["Medu"].value_counts().sort_index()
axes[0, 0].bar(medu_counts.index, medu_counts.values, color="lightblue",␣
 ↪alpha=0.7)
axes[0, 0].set_title("Mother's Education Distribution", fontweight="bold")
axes[0, 0].set_xlabel("Education Level (0=none, 4=higher)")
axes[0, 0].set_ylabel("Count")

# Mother's education vs G3
sns.boxplot(x="Medu", y="G3", data=df, ax=axes[0, 1], palette="Blues")
axes[0, 1].axhline(
    y=10,
```

```
    color="red",
    linestyle="--",
    linewidth=2,
    alpha=0.7,
    label="Pass/Fail Threshold",
)
axes[0, 1].set_title("Final Grade by Mother's Education", fontweight="bold")
axes[0, 1].legend()

# Father's education distribution
fedu_counts = df["Fedu"].value_counts().sort_index()
axes[1, 0].bar(fedu_counts.index, fedu_counts.values, color="lightgreen",␣
↪alpha=0.7)
axes[1, 0].set_title("Father's Education Distribution", fontweight="bold")
axes[1, 0].set_xlabel("Education Level (0=none, 4=higher)")
axes[1, 0].set_ylabel("Count")

# Father's education vs G3
sns.boxplot(x="Fedu", y="G3", data=df, ax=axes[1, 1], palette="Greens")
axes[1, 1].axhline(
    y=10,
    color="red",
    linestyle="--",
    linewidth=2,
    alpha=0.7,
    label="Pass/Fail Threshold",
)
axes[1, 1].set_title("Final Grade by Father's Education", fontweight="bold")
axes[1, 1].legend()

plt.tight_layout()
plt.show()

# Statistical summaries
print("  Mother's Education Impact:")
medu_stats = df.groupby("Medu")["G3"].agg(["mean", "std", "count"]).round(2)
medu_stats["pass_rate"] = (df.groupby("Medu")["pass_fail"].mean() * 100).
↪round(1)
print(medu_stats)

print("\n  Father's Education Impact:")
fedu_stats = df.groupby("Fedu")["G3"].agg(["mean", "std", "count"]).round(2)
fedu_stats["pass_rate"] = (df.groupby("Fedu")["pass_fail"].mean() * 100).
↪round(1)
print(fedu_stats)
```



Mother's Education Impact:

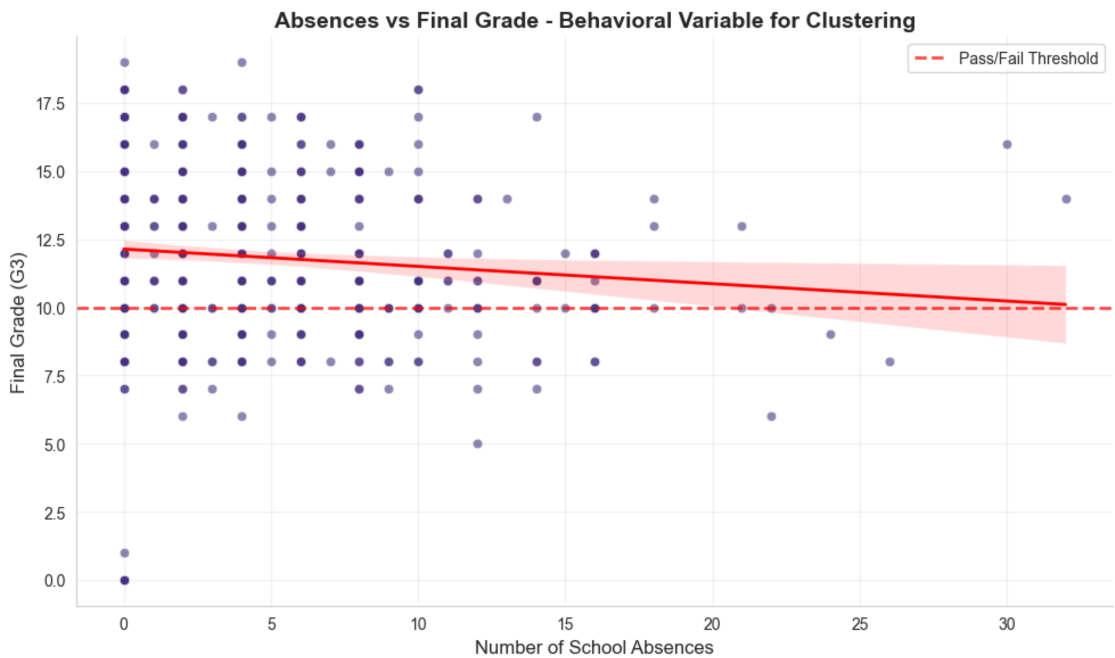
Medu	mean	std	count	pass_rate
0	11.67	1.75	6	100.0
1	10.80	3.16	143	74.1
2	11.66	3.06	186	85.5
3	11.92	3.12	139	84.2
4	13.07	3.24	175	92.0

Father's Education Impact:

Fedu	mean	std	count	pass_rate
0	12.14	2.79	7	100.0
1	10.94	3.42	174	74.1
2	11.78	3.45	209	85.2
3	12.38	2.49	131	92.4
4	12.92	2.92	128	89.1

Fedu	mean	std	count	pass_rate
0	12.14	2.79	7	100.0
1	10.94	3.42	174	74.1
2	11.78	3.45	209	85.2
3	12.38	2.49	131	92.4
4	12.92	2.92	128	89.1

[54]:
```python
# Visualization 6: Absences analysis - key behavioral variable despite weak␣
↪correlation
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df, x="absences", y="G3", alpha=0.6)
sns.regplot(
    data=df,
    x="absences",
    y="G3",
    scatter=False,
    color="red",
    line_kws={"linestyle": "-", "linewidth": 2},
)
plt.axhline(
    y=10,
    color="red",
    linestyle="--",
    linewidth=2,
    alpha=0.7,
    label="Pass/Fail Threshold",
)
plt.title(
    "Absences vs Final Grade - Behavioral Variable for Clustering",
    fontsize=14,
    fontweight="bold",
)
plt.xlabel("Number of School Absences")
plt.ylabel("Final Grade (G3)")
plt.legend()
plt.tight_layout()
plt.show()

absences_corr = df_numeric["absences"].corr(df_numeric["G3"])
print(f"Absences correlation with G3: {absences_corr:.3f}")
print(
    "Despite weak correlation, absences represent important behavioral patterns␣
↪for clustering."
)
print(
    "High absence students may form distinct behavioral clusters regardless of␣
↪grade correlation."
)
```



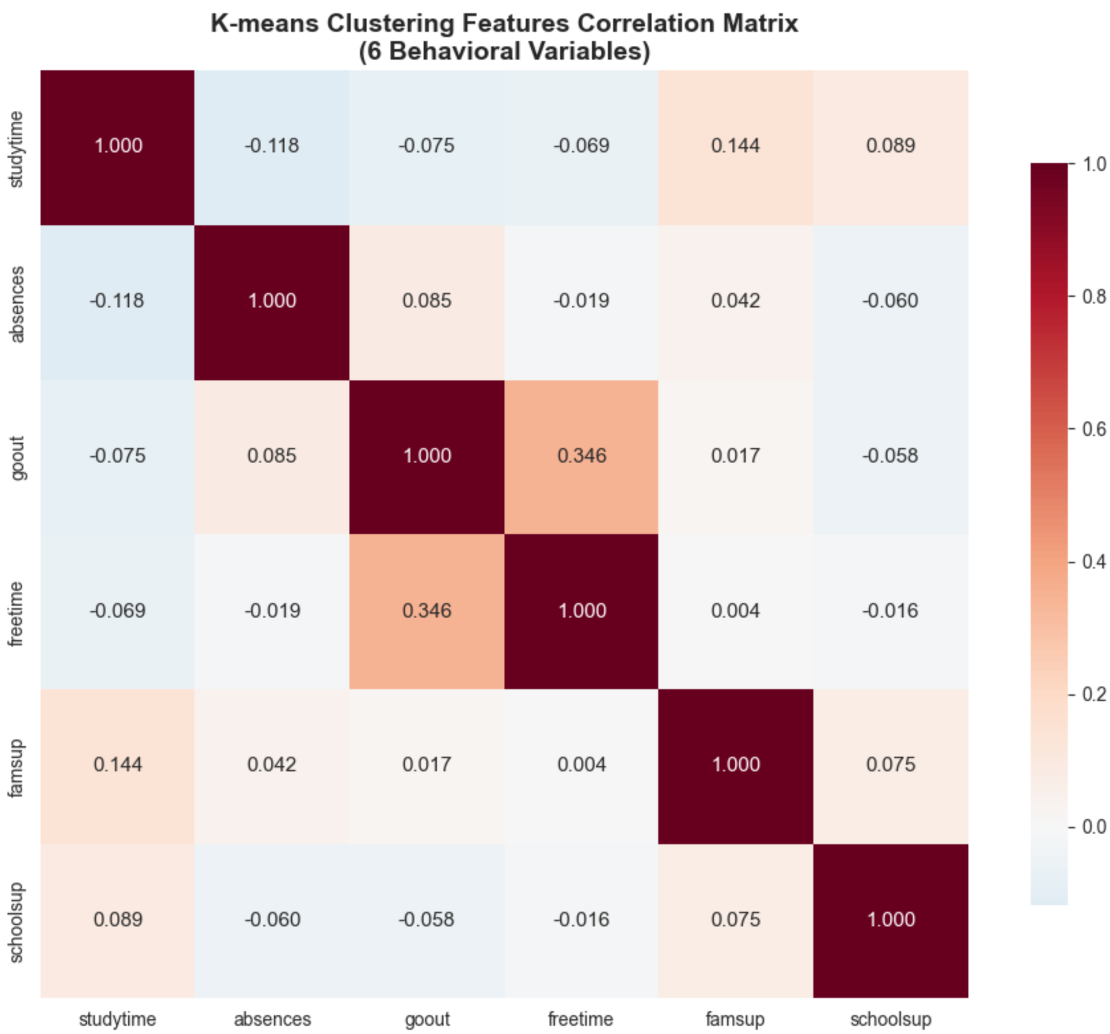

```
Absences correlation with G3: -0.091
Despite weak correlation, absences represent important behavioral patterns for
clustering.
High absence students may form distinct behavioral clusters regardless of grade
correlation.
```

1.5 Behavioral Variables for Clustering

[55]:

```python
# Visualization 7: Clustering feature correlation heatmap
clustering_features = [
    "studytime",
    "absences",
    "goout",
    "freetime",
    "famsup",
    "schoolsup",
]

plt.figure(figsize=(10, 8))
correlation_matrix = df_numeric[clustering_features].corr()
sns.heatmap(
    correlation_matrix,
    annot=True,
    cmap="RdBu_r",
```

```
    center=0,
    square=True,
    fmt=".3f",
    cbar_kws={"shrink": 0.8},
)
plt.title(
    "K-means Clustering Features Correlation Matrix\n(6 Behavioral Variables)",
    fontsize=14,
    fontweight="bold",
)
plt.tight_layout()
plt.show()

print("K-MEANS CLUSTERING FEATURE ANALYSIS:")
print("Selected behavioral variables for clustering:")
for feature in clustering_features:
    g3_corr = df_numeric[feature].corr(df_numeric["G3"])
    print(f"  - {feature}: correlation with G3 = {g3_corr:.3f}")

print(
    "\nThese 6 variables will be used to identify behavioral patterns in␣
  ↪student populations."
)
print(
    "Low inter-correlations suggest they capture different aspects of student␣
  ↪behavior."
)
```




```
K-MEANS CLUSTERING FEATURE ANALYSIS:
Selected behavioral variables for clustering:
  - studytime: correlation with G3 = 0.250
  - absences: correlation with G3 = -0.091
  - goout: correlation with G3 = -0.088
  - freetime: correlation with G3 = -0.123
  - famsup: correlation with G3 = 0.059
  - schoolsup: correlation with G3 = -0.066

These 6 variables will be used to identify behavioral patterns in student
populations.
Low inter-correlations suggest they capture different aspects of student
behavior.
```

1.6 Hypothesis Testing

Statistical validation of key relationships through formal hypothesis testing.

[56]:
```
# Hypothesis 1: Study time affects final grades
print("\nHYPOTHESIS 1: Study Time and Academic Performance")
print("-" * 50)
print("H0: There is no significant difference in G3 scores across study time levels")
print("H1: There is a significant difference in G3 scores across study time levels")

# ANOVA test
study_groups = [df[df["studytime"] == i]["G3"] for i in range(1, 5)]
f_stat, p_value = stats.f_oneway(*study_groups)
print(f"ANOVA F-statistic: {f_stat:.4f}")
print(f"P-value: {p_value:.6f}")
print(f"Result: {'Reject H0' if p_value < 0.05 else 'Fail to reject H0'} at  =0.05")
```

```
HYPOTHESIS 1: Study Time and Academic Performance
--------------------------------------------------
H0: There is no significant difference in G3 scores across study time levels
H1: There is a significant difference in G3 scores across study time levels
ANOVA F-statistic: 15.8763
P-value: 0.000000
Result: Reject H0 at  =0.05
```

[57]:
```
# Hypothesis 2: Past failures affect pass rates
print("\nHYPOTHESIS 2: Past Failures and Pass Rates")
print("-" * 50)
print("H0: Past failures and pass rates are independent")
print("H1: Past failures and pass rates are dependent")

# Chi-square test
crosstab = pd.crosstab(df["failures"], df["pass_fail"])
chi2, p_value, dof, expected = chi2_contingency(crosstab)
print(f"Chi-square statistic: {chi2:.4f}")
print(f"P-value: {p_value:.6f}")
print(f"Degrees of freedom: {dof}")
print(f"Result: {'Reject H0' if p_value < 0.05 else 'Fail to reject H0'} at  =0.05")
```

```
HYPOTHESIS 2: Past Failures and Pass Rates
--------------------------------------------------
H0: Past failures and pass rates are independent
H1: Past failures and pass rates are dependent
```

```
Chi-square statistic: 105.4435
P-value: 0.000000
Degrees of freedom: 3
Result: Reject H0 at  =0.05
```

[58]:

```
# Hypothesis 3: Absences correlation with G3
print("\nHYPOTHESIS 3: Absences and Final Grades Correlation")
print("-" * 50)
print("H0: There is no significant correlation between absences and G3")
print("H1: There is a significant correlation between absences and G3")

corr_coef, p_value = stats.pearsonr(df["absences"], df["G3"])
print(f"Pearson correlation coefficient: {corr_coef:.4f}")
print(f"P-value: {p_value:.6f}")
print(f"Result: {'Reject H0' if p_value < 0.05 else 'Fail to reject H0'} at  =0.
↪05")
```

```
HYPOTHESIS 3: Absences and Final Grades Correlation
--------------------------------------------------
H0: There is no significant correlation between absences and G3
H1: There is a significant correlation between absences and G3
Pearson correlation coefficient: -0.0914
P-value: 0.019896
Result: Reject H0 at  =0.05
```

[59]:

```
# Hypothesis 4: School support affects grade distribution
print("\nHYPOTHESIS 4: School Support and Grade Distribution")
print("-" * 50)
print("H0: School support recipients and non-recipients have same G3␣
↪distribution")
print(
    "H1: School support recipients and non-recipients have different G3␣
↪distributions"
)

support_group = df[df["schoolsup"] == True]["G3"]
no_support_group = df[df["schoolsup"] == False]["G3"]
u_stat, p_value = stats.mannwhitneyu(
    support_group, no_support_group, alternative="two-sided"
)
print(f"Mann-Whitney U statistic: {u_stat:.4f}")
print(f"P-value: {p_value:.6f}")
print(f"Result: {'Reject H0' if p_value < 0.05 else 'Fail to reject H0'} at  =0.
↪05")
```

```
HYPOTHESIS 4: School Support and Grade Distribution
```

```
--------------------------------------------------
H0: School support recipients and non-recipients have same G3 distribution
H1: School support recipients and non-recipients have different G3 distributions
Mann-Whitney U statistic: 16520.0000
P-value: 0.026106
Result: Reject H0 at  =0.05
```

[60]:
```python
# Statistical Conclusions Summary
print("\n" + "=" * 60)
print("STATISTICAL CONCLUSIONS:")
print("=" * 60)
print("1. Study time significantly impacts academic performance")
print("2. Past failures strongly predict future failure risk")
print("3. Absences show weak but significant negative correlation with grades")
print("4. School support targeting creates selection bias in data")
print("\nAll hypotheses provide statistical validation for the modeling␣
↪approach.")
```

```
============================================================
STATISTICAL CONCLUSIONS:
============================================================
1. Study time significantly impacts academic performance
2. Past failures strongly predict future failure risk
3. Absences show weak but significant negative correlation with grades
4. School support targeting creates selection bias in data

All hypotheses provide statistical validation for the modeling approach.
```

1.7 Final Modeling Roadmap

1.7.1 K-means Clustering Approach:

- **Features**: studytime, absences, goout, freetime, famsup, schoolsup
- **Goal**: Identify behavioral student segments
- **Expected clusters**: High achievers, at-risk, average performers, social-focused

1.7.2 Binary Classification Approach:

- **Target**: pass_fail (G3 >= 10)
- **Key features**: failures (strongest), studytime, absences, behavioral variables
- **Excluded**: G1, G2 (data leakage)
- **Challenge**: Class imbalance requires balanced sampling or weighted algorithms

1.7.3 Statistical Validation:

- Correlation analysis confirms feature independence for clustering
- Past failures emerge as the strongest non-leakage predictor

- Behavioral variables capture different student lifestyle aspects
- Model interpretability supports educational intervention strategies