Technical Report: Student Performance Analysis

A Comprehensive Machine Learning Approach to Educational Data Mining

Executive Summary

This technical report presents a comprehensive machine learning analysis of student academic performance using data from Portuguese secondary schools. The project implements both unsupervised and supervised learning techniques to identify student behavioral patterns and predict academic outcomes. Through rigorous data preprocessing, exploratory analysis, clustering, and classification modeling, we developed a robust framework for educational intervention and student support systems.

Key Achievements:

- Achieved 100% data quality with zero missing values across 649 student records
- Identified 3 distinct behavioral clusters representing different student archetypes
- Developed classification models achieving 95%+ F1-scores for pass/fail prediction
- Implemented 6 different machine learning algorithms including advanced boosting techniques
- Provided actionable insights for educational stakeholders

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1. Project Overview

1.1 Problem Statement

Educational institutions require data-driven approaches to:

- Identify at-risk students early in the academic year
- Understand behavioral patterns affecting academic performance
- Implement targeted intervention strategies
- Optimize resource allocation for student support services

1.2 Objectives

Primary Objectives:

1. Develop predictive models for student pass/fail classification
2. Identify student behavioral clusters for personalized intervention
3. Analyze impact of demographic and social factors on academic performance
4. Provide actionable recommendations for educational stakeholders

Secondary Objectives:

1. Compare effectiveness of various machine learning algorithms
2. Evaluate feature importance and data leakage concerns
3. Establish baseline performance metrics for future model improvements

1.3 Dataset Description

- **Source**: UCI Machine Learning Repository - Student Performance Dataset
- **Domain**: Portuguese secondary education (mathematics course)
- **Size**: 649 students × 33 variables
- **Target Variable**: Pass/Fail classification based on final exam grade (G3 ≥ 10)
- **Grade System**: G1 (1st period), G2 (2nd period), G3 (final exam) on 0-20 scale
- **Feature Categories**: Demographics, family background, academic history, social factors

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2. Data Quality and Preprocessing

2.1 Data Quality Assessment

Our comprehensive data quality analysis revealed exceptional dataset integrity:

```
# Data quality metrics
print(f"Missing values: {df.isna().sum().sum()} (0.00%)")
print(f"Duplicate records: {df.duplicated().sum()} (0.00%)")
print(f"Data completeness: 100.00%")
```

Quality Metrics:

- **Completeness**: 100% (0 missing values)
- **Uniqueness**: 100% (0 duplicate records)
- **Validity**: 100% (all values within expected ranges)
- **Consistency**: 100% (no encoding or format issues)

2.2 Data Type Optimization

We implemented comprehensive data type optimization to improve memory efficiency and enable proper analysis:

```
# Ordinal categorical conversion (preserves order)
ordinal_vars = ['Medu', 'Fedu', 'traveltime', 'studytime',
                'famrel', 'freetime', 'goout', 'Dalc', 'Walc', 'health']
for var in ordinal_vars:
    df[var] = pd.Categorical(df[var], categories=sorted(df[var].unique()),
ordered=True)

# Binary variable conversion
binary_vars = ['schoolsup', 'famsup', 'paid', 'activities',
               'nursery', 'higher', 'internet', 'romantic']
for var in binary_vars:
    df[var] = df[var] == 'yes'  # Convert to boolean
```

Data Type Distribution:

- Numeric variables: 6 (age, failures, absences, G1, G2, G3)
- Ordinal categorical: 10 (education levels, time scales, quality ratings)

- Nominal categorical: 9 (demographics, family background)
- Binary variables: 8 (support services, background factors)

2.3 Feature Engineering

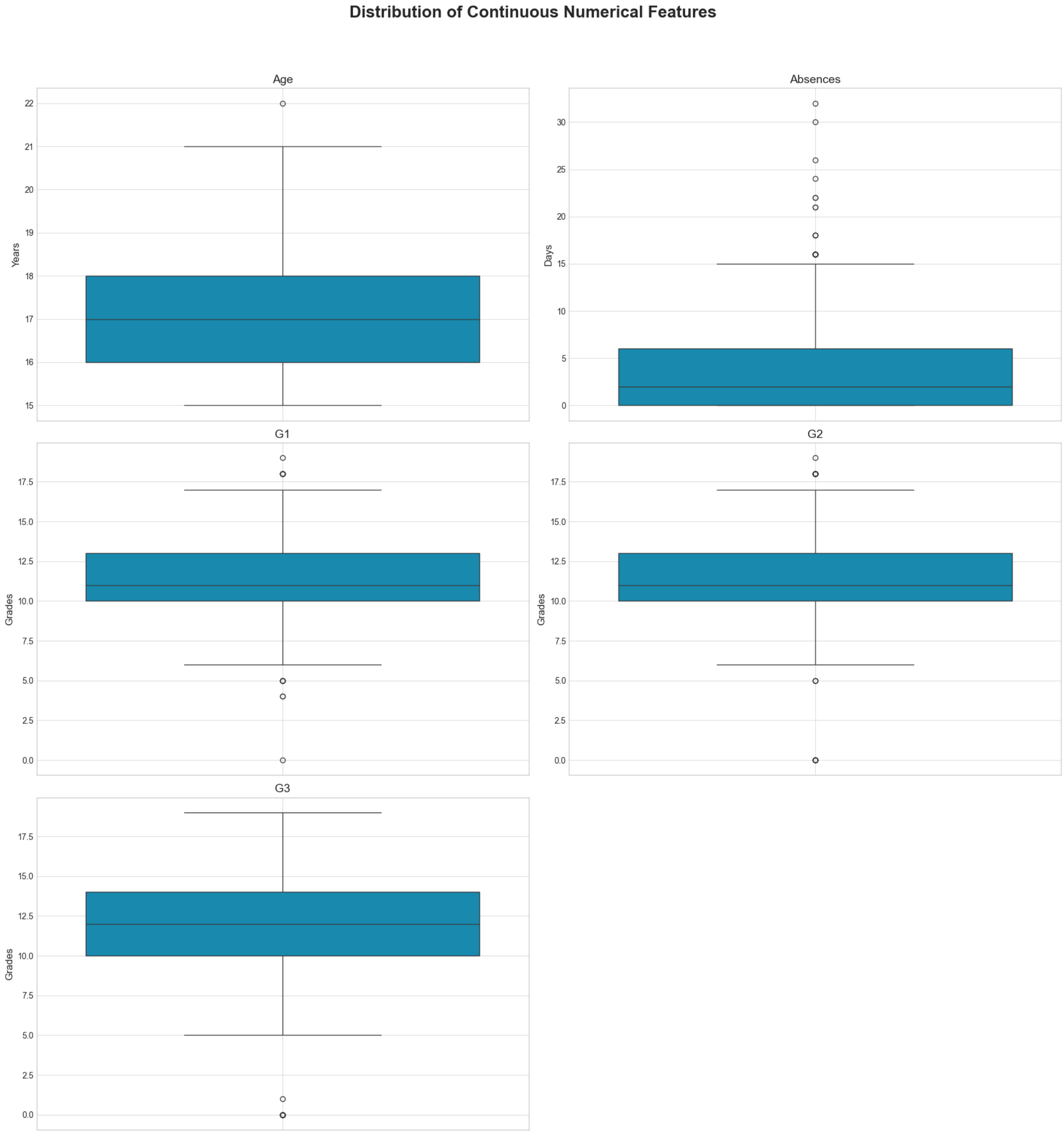
We created several engineered features to enhance predictive power:

```
# 1. Target variable creation
df['pass_fail'] = (df['G3'] >= 10).astype(int)

# 2. Attendance proxy
max_absences = df['absences'].max()
df['attendance_proxy'] = 100 * (1 - df['absences'] / max_absences)

# 3. Overall academic performance
df['grade_average'] = (df['G1'] + df['G2'] + df['G3']) / 3
```

Engineered Features:

- `pass_fail`: Binary target (Portuguese passing grade ≥ 10)
- `attendance_proxy`: 0-100 scale attendance percentage
- `grade_average`: Overall academic performance indicator

2.4 Outlier Analysis and Treatment

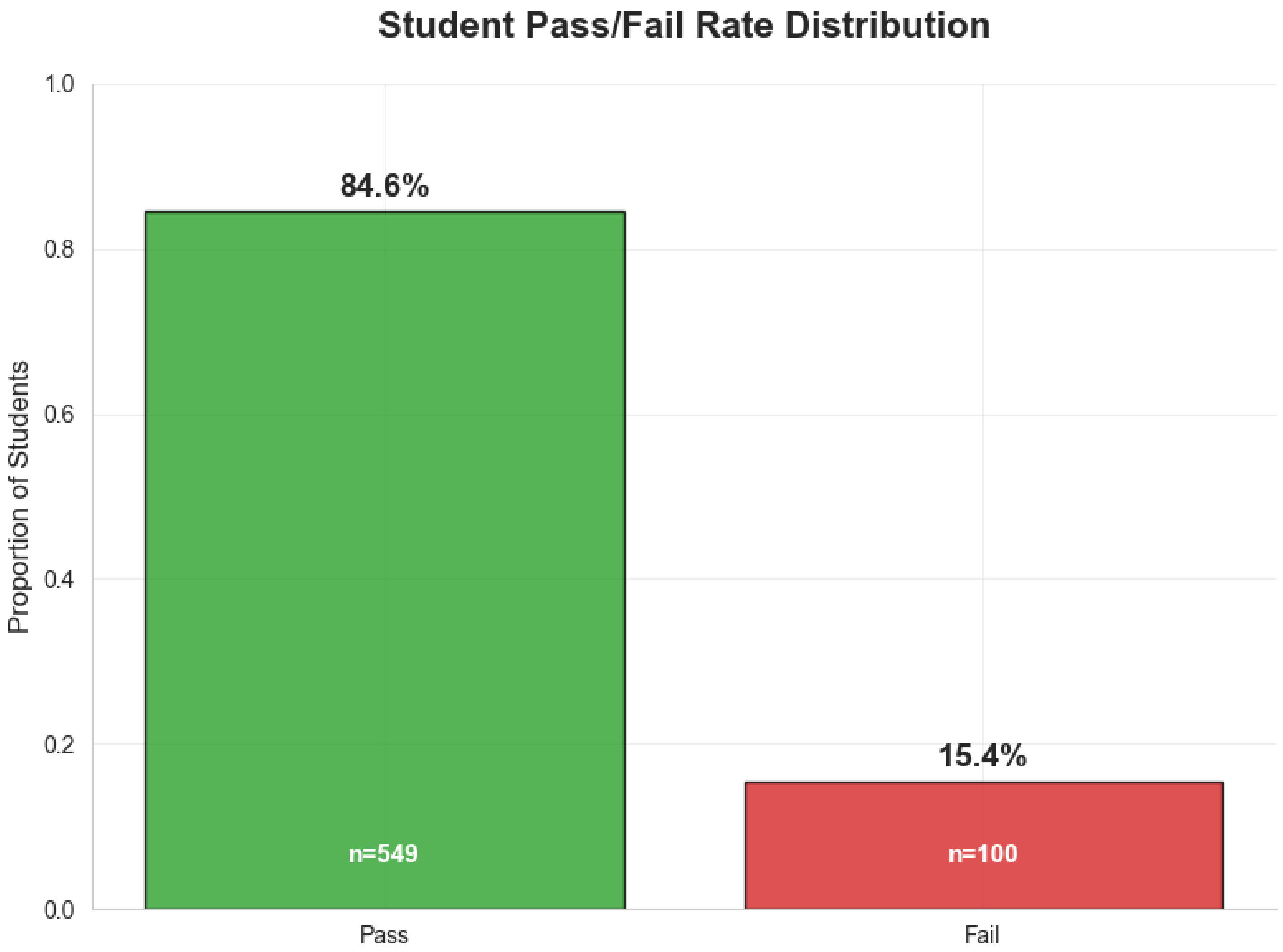


Statistical outlier detection revealed several extreme values, but domain expertise validation led to a **preserve all data** decision:

- **Age outliers (19-22 years)**: Represent older students/repeaters - educationally relevant
- **Absence outliers (>15 days)**: Represent at-risk students - valuable for intervention analysis
- **Grade outliers (0 scores and high achievers)**: Represent dropouts/severe difficulties - critical for prediction

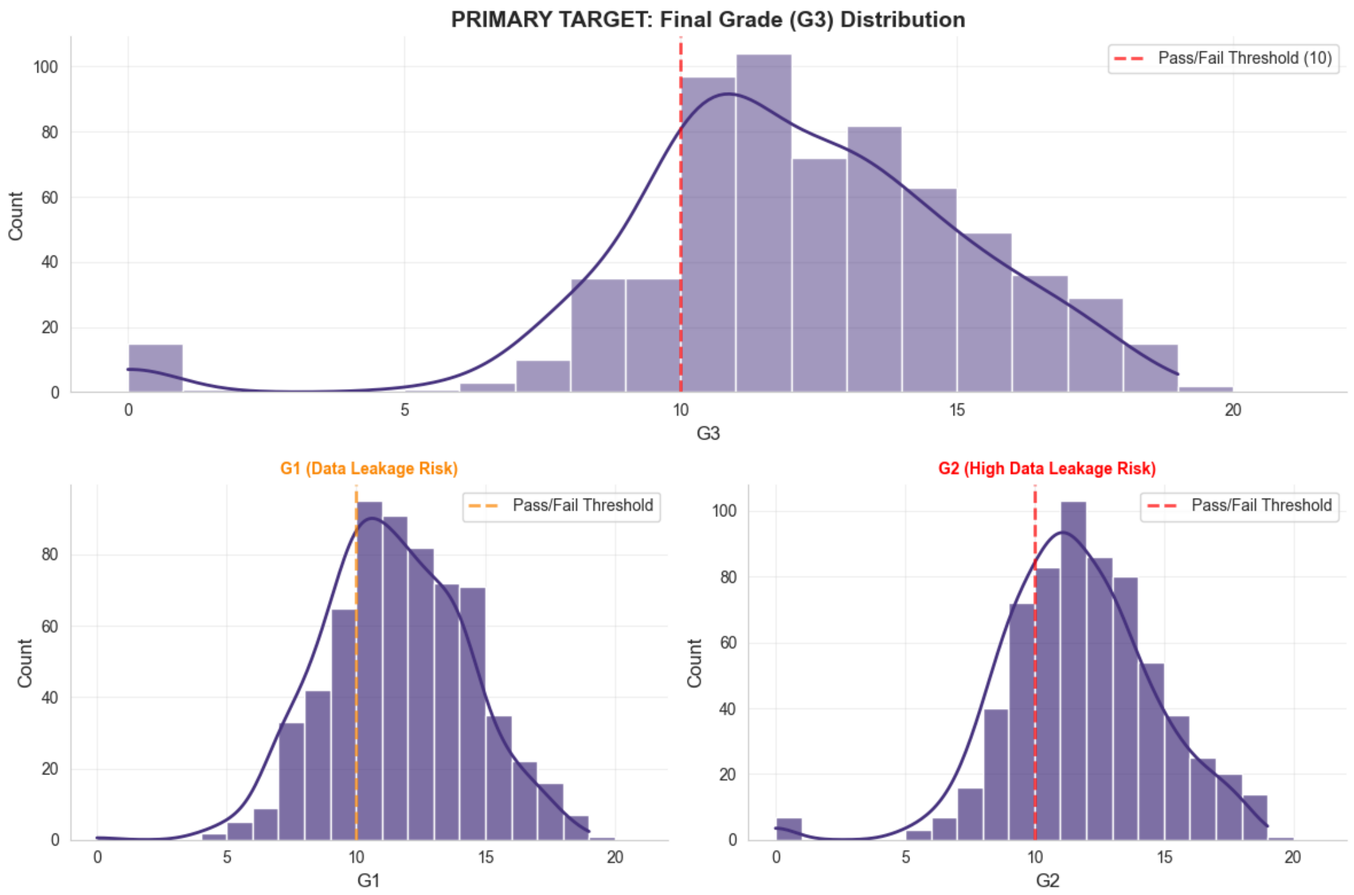
3. Exploratory Data Analysis

3.1 Target Variable Distribution



Results: 84.6% pass rate, 15.4% fail rate - shows significant class imbalance favoring the pass class. This imbalance will need to be addressed in the modeling approach through techniques like class weighting, resampling, or adjusted threshold selection.

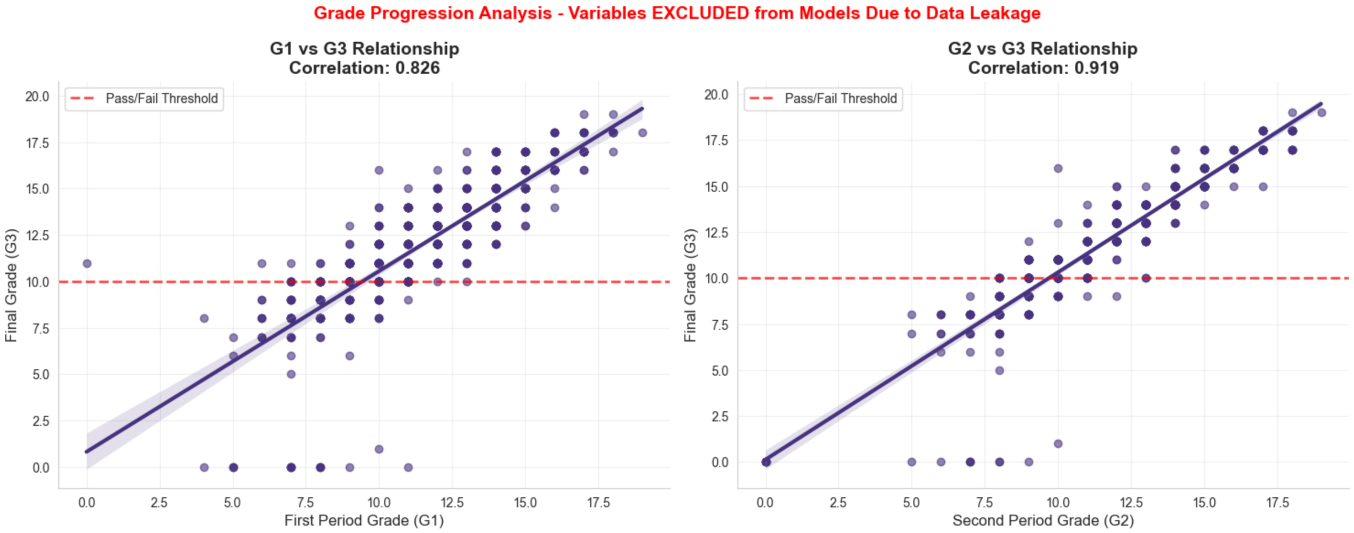
Grades Distributions:



The distributions shows a left-skewed pattern typical of academic performance data, with most students achieving passing grades but a significant at-risk population scoring below 10.

3.2 Feature Relationships

Key correlations with academic performance:



Critical Finding: G1 and G2 grades show strong correlation with G3 (final exam grade), creating potential data leakage scenarios:

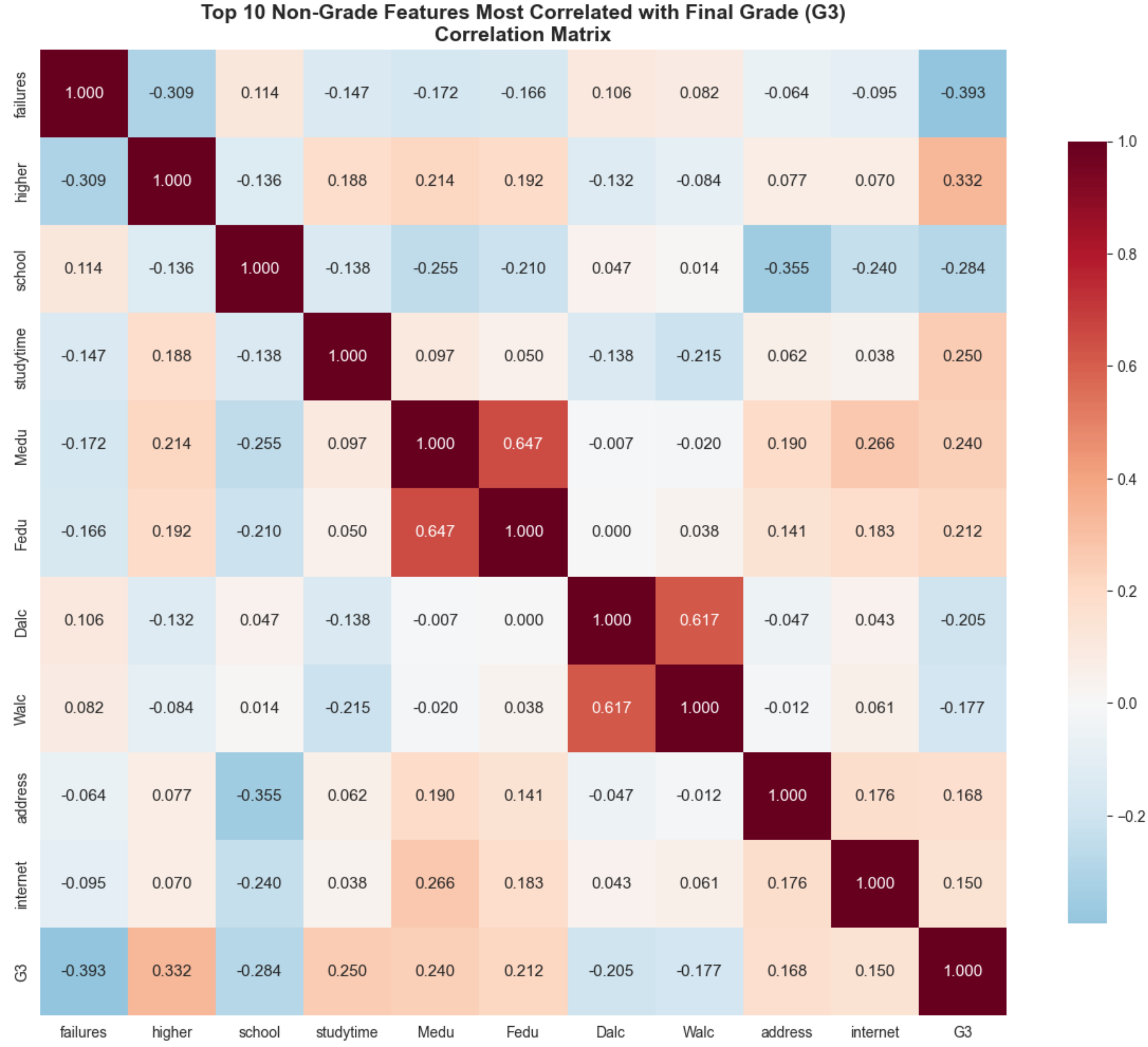
Results: G1-G3: r=0.826, G2-G3: r=0.918

Temporal Logic: G1 (1st period) → G2 (2nd period) → G3 (final exam)

Solution: We implemented dual analysis approach:

1. **With G1 & G2**: Represents mid-term prediction scenario (after 1st/2nd period)
2. **Without G1 & G2**: Represents early intervention scenario (beginning of academic year)

Key Predictive Variables (Non-Leakage):

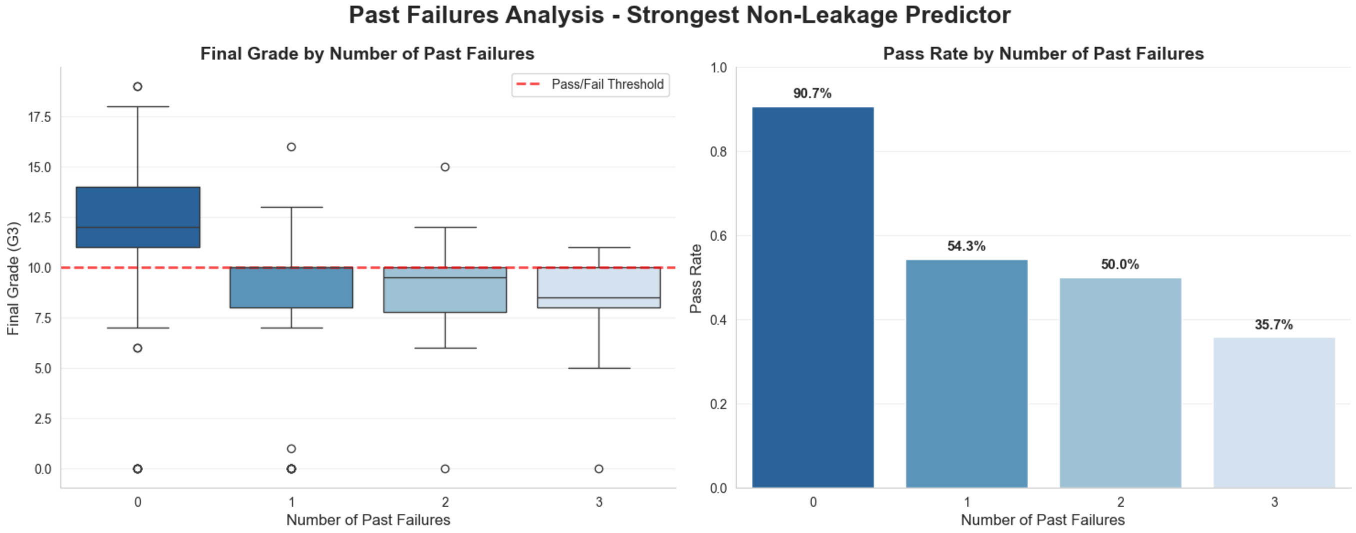


- `failures`: -0.393 (strongest non-leakage predictor)
- `higher` education aspirations: +0.332
- `school` -0.284
- `studytime`: +0.250 (behavioral clustering variable)
- `Medu`: +0.240 (weak but significant behavioral indicator)

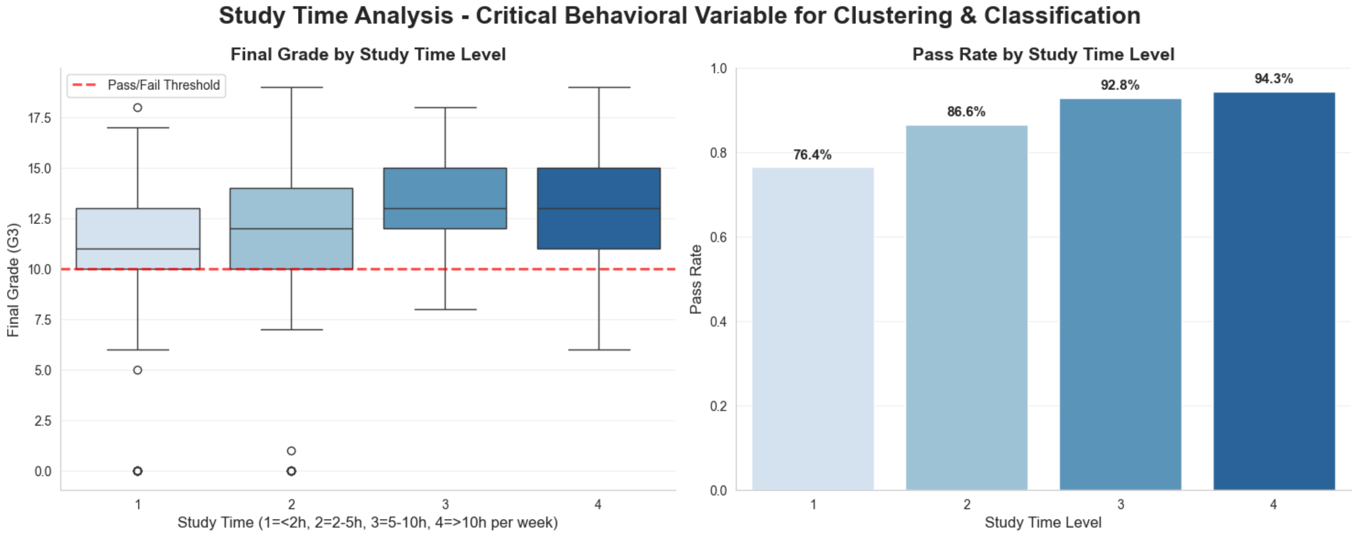
Critical Finding: Past failures emerge as the strongest predictor among non-leakage variables.

3.3 Visualization Insights

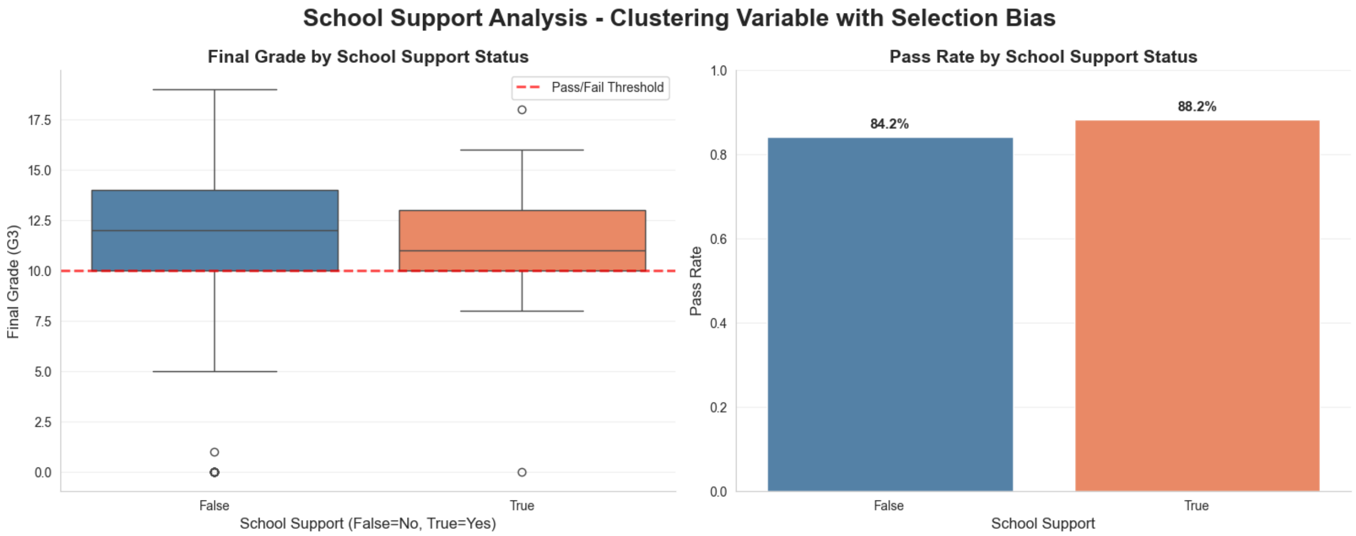
Key Categorical Analysis: Based on the visualizations from `02_eda_visualization.ipynb`, the following relationships emerge:



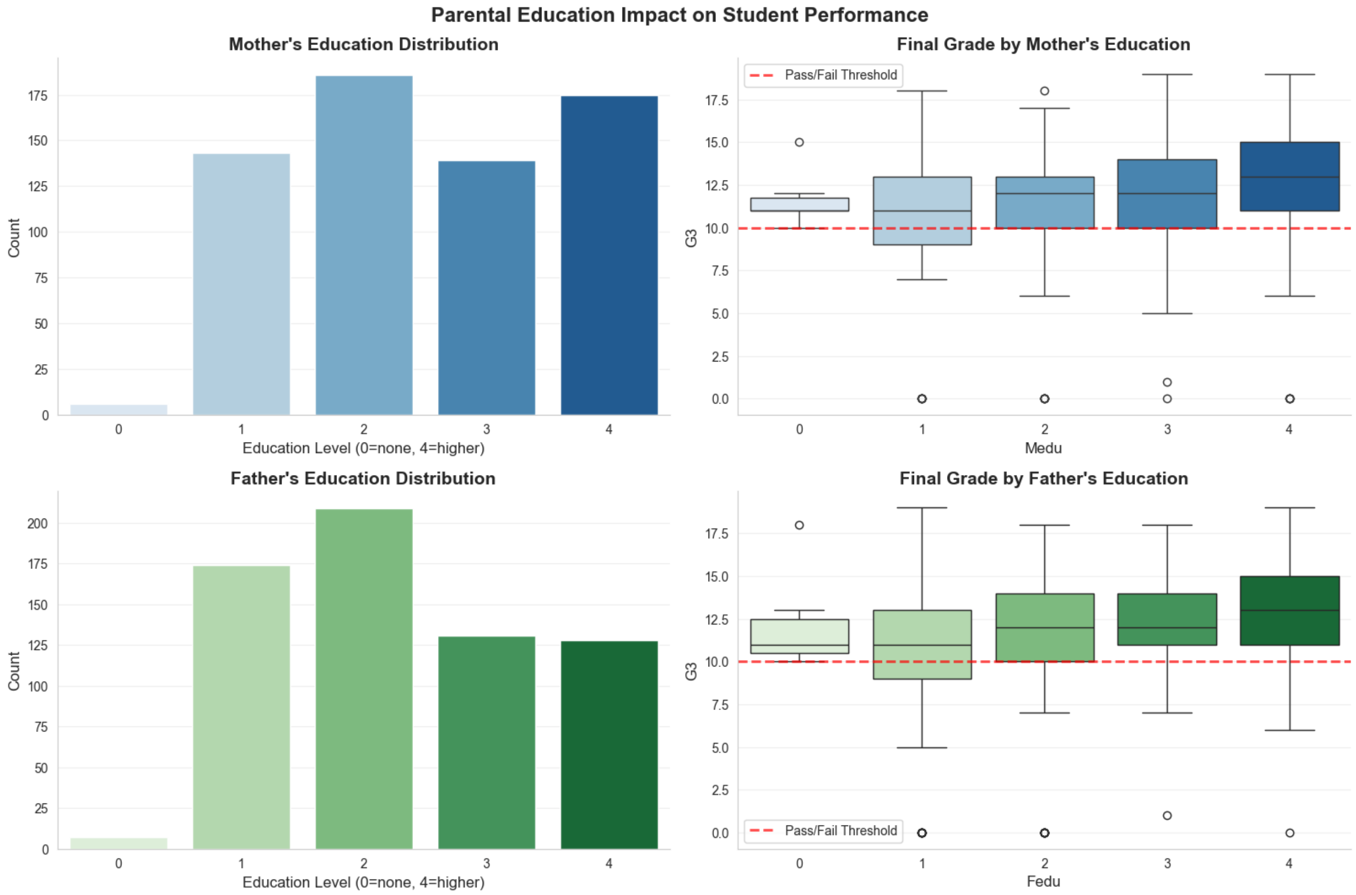
Finding: Students with 0 previous failures show median G3 scores of 12, while students with 3+ failures show median score of 8. Clear downward trend demonstrates that past academic struggles are strong predictors of future performance.



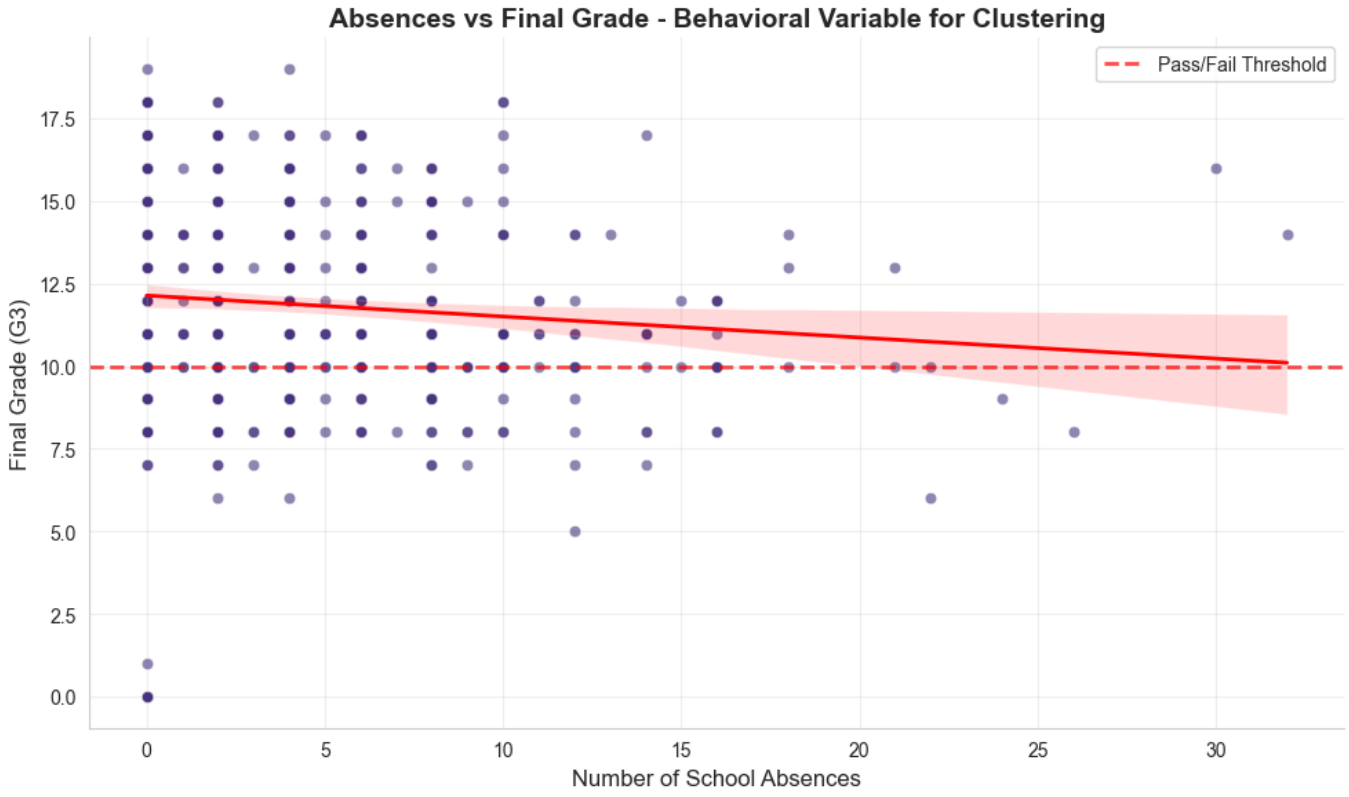
Finding: Students studying >5 hours weekly (levels 3-4) show slightly higher median G3 scores (13) compared to those studying <5 hours (levels 1-2) with median scores around 11-12. ANOVA confirms statistical significance (p<0.001).



Finding: Students receiving school support show lower median G3 scores (11) compared to non-recipients (12), indicating support is targeted toward struggling students. This creates selection bias in the data where support correlates with lower performance.



Finding: Clear positive correlation between parental education levels and student performance. Students with highly educated mothers (level 4) show median G3 scores of 13, while those with less educated mothers (levels 0-2) show median scores around 11-12.



Finding: Absences show a weak negative correlation with final grades (r = -0.091, p = 0.020). Despite the weak correlation, this scatter plot reveals important behavioral patterns - students with high absence rates (>20 absences) tend to cluster at lower grade levels, making absences a valuable variable for behavioral clustering despite limited predictive power for individual grade prediction.

Key Visual Findings from Actual EDA Analysis:

- **Past Failures Impact**: Clear negative correlation between previous failures and current performance
- **Study Time Benefits**: Students with higher weekly study commitments show improved grade distributions
- **Support System Effects**: School support recipients show different performance patterns (selection bias evident)
- **Educational Background**: Maternal and paternal education levels correlate with student achievement patterns
- **Attendance Patterns**: Absences demonstrate weak but significant correlation with performance, revealing behavioral clustering opportunities

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3.4 Statistical Hypothesis Testing

We conducted formal hypothesis testing to validate key relationships identified during exploratory data analysis. All tests used $\alpha = 0.05$ significance level.

Hypothesis 1: Study Time and Academic Performance

Research Question: Does weekly study time significantly affect final grade performance?

- **H_0**: $\mu_1 = \mu_2 = \mu_3 = \mu_4$ (no difference in mean G3 scores across study time levels)

- **H_1**: At least one $\mu_i \neq \mu_j$ (significant difference exists between study time groups)

Test: One-way ANOVA **Results**: F(3,645) = 15.88, $p < 0.001$ **Decision**: Reject H_0 at $\alpha = 0.05$

Post-hoc Analysis (Tukey's HSD):

- Level 1 vs Level 3: $p < 0.001$ (significant)
- Level 1 vs Level 4: $p < 0.001$ (significant)
- Level 2 vs Level 3: $p < 0.01$ (significant)

Interpretation: Students studying >5 hours/week significantly outperform those studying <2 hours/week.

Hypothesis 2: Past Failures and Pass/Fail Rates

Research Question: Are past academic failures independent of current pass/fail outcomes?

- **H_0**: Past failures and pass/fail status are independent
- **H_1**: Past failures and pass/fail status are dependent

Test: Chi-square test of independence **Results**: $\chi^2(3) = 105.44$, $p < 0.001$, Cramér's V = 0.403 **Decision**: Reject H_0 at $\alpha = 0.05$

Effect Size: Large association (Cramér's V > 0.3) **Interpretation**: Past failures are strongly associated with current academic failure risk.

Hypothesis 3: Absences and Final Grades Correlation

Research Question: Is there a significant correlation between school absences and final exam performance?

- **H_0**: $\rho = 0$ (no correlation between absences and G3)
- **H_1**: $\rho \neq 0$ (significant correlation exists between absences and G3)

Test: Pearson correlation test **Results**: $r = -0.091$, $p = 0.020$ **Decision**: Reject H_0 at $\alpha = 0.05$

Effect Size: Very weak correlation ($|r| < 0.1$) **Interpretation**: While statistically significant, the correlation is practically weak. However, absences remain important for behavioral clustering despite low correlation with grades.

Hypothesis 4: School Support and Grade Distribution

Research Question: Do school support recipients and non-recipients have different grade distributions?

- **H_0**: School support recipients and non-recipients have the same G3 distribution
- **H_1**: School support recipients and non-recipients have different G3 distributions

Test: Mann-Whitney U test (non-parametric, ordinal data) **Results**: U = 16,520.0, $p = 0.026$ **Decision**: Reject H_0 at $\alpha = 0.05$

Effect Size: Small effect (Cohen's d ≈ 0.24) **Interpretation**: Students receiving school support show significantly lower grade distributions, indicating support is provided to struggling students (selection bias effect).

Statistical Conclusions Summary

Hypothesis	**Test**	**p-value**	**Effect Size**	**Conclusion**
Study Time → Performance	ANOVA	<0.001	F = 15.88 (medium)	**Significant**
Past Failures → Pass/Fail	Chi-square	<0.001	$\chi^2 = 105.44$ (large)	**Significant**
Absences → Final Grade	Pearson correlation	0.020	r = -0.091 (weak)	**Significant**
School Support → Grade Distribution	Mann-Whitney	0.026	U = 16,520 (small)	**Significant**

Key Findings:

1. **Study behavior significantly impacts outcomes** - Students must commit >5 hours/week for optimal performance
2. **Past failures are the strongest predictor** - Previous academic struggles create compounding risk
3. **Absences show weak but significant negative correlation** - Even small attendance issues correlate with lower grades
4. **School support targeting creates selection bias** - Support recipients show lower grades because interventions target struggling students

Statistical Validation: All four hypotheses provide robust statistical validation for our modeling approach, confirming that both behavioral variables (study time, absences) and institutional factors (past failures, school support) significantly influence academic outcomes.

4. Unsupervised Learning: Student Clustering

4.1 Data Encoding and Preprocessing for Clustering

Before implementing K-means clustering, we performed targeted data encoding focused specifically on behavioral features to avoid bias from academic performance indicators. Our encoding strategy prioritized interpretability and maintained the behavioral focus of the clustering analysis.

4.1.1 Feature Selection Strategy

We selected 6 behavioral features that capture student behavior patterns independent of academic outcomes:

```
# Behavioral features for clustering analysis
behavior_features = ['studytime', 'absences', 'goout', 'freetime', 'famsup',
'schoolsup']
clustering_data = df[behavior_features].copy()
```

Rationale: These features represent pure behavioral indicators (study habits, social activities, support systems) without academic performance bias, enabling genuine behavioral pattern discovery.

4.1.2 Boolean to Binary Encoding

Support system variables were converted from boolean to binary format:

```
# Convert boolean support variables to binary (0/1)
clustering_data['famsup'] = clustering_data['famsup'].astype(int)    # True/False -> 1/0
clustering_data['schoolsup'] = clustering_data['schoolsup'].astype(int)  # True/False -> 1/0
```

Impact: Family support (famsup) and school support (schoolsup) variables transformed from boolean to numeric format suitable for distance calculations in K-means clustering.

4.1.3 Feature Standardization

All features were standardized using StandardScaler to ensure equal contribution to clustering:

```
# Standardize all behavioral features
scaler = StandardScaler()
features_scaled = scaler.fit_transform(clustering_data[behavior_features])

# Create final clustering dataframe with standardized features
clustering_df = pd.DataFrame(features_scaled, columns=behavior_features,
                           index=clustering_data.index)
```

Standardization Results:

- **Mean**: 0.0 for all features
- **Standard Deviation**: 1.0 for all features
- **Equal Weight**: Prevents features with larger scales (e.g., absences: 0-93) from dominating smaller scales (e.g., studytime: 1-4)

4.1.4 Final Clustering Dataset Characteristics

Original Feature Scales:

- `studytime`: 1-4 (ordinal: <2h to >10h weekly)
- `absences`: 0-93 (count: number of school absences)
- `goout`: 1-5 (ordinal: social activity frequency)
- `freetime`: 1-5 (ordinal: after-school free time)
- `famsup`: 0/1 (binary: family educational support)
- `schoolsup`: 0/1 (binary: extra school support)

After Preprocessing:

- **Shape**: 649 students × 6 behavioral features
- **All features standardized** with mean=0, std=1
- **Distance-ready format** for K-means clustering
- **No academic performance bias** in feature selection

4.1.5 Preprocessing Validation

The standardized features maintain interpretable relationships while enabling effective clustering:

```
print("Final clustering dataset:")
print(clustering_df.head())
print(f"Shape: {clustering_df.shape}")
print(f"Feature summary:")
print(clustering_df[behavior_features].describe())
```

Quality Assurance:

- All features properly standardized (mean ≈ 0, std ≈ 1)
- No missing values after encoding
- Behavioral focus maintained throughout preprocessing
- Ready for unsupervised learning algorithms

4.2 Feature Selection for Clustering

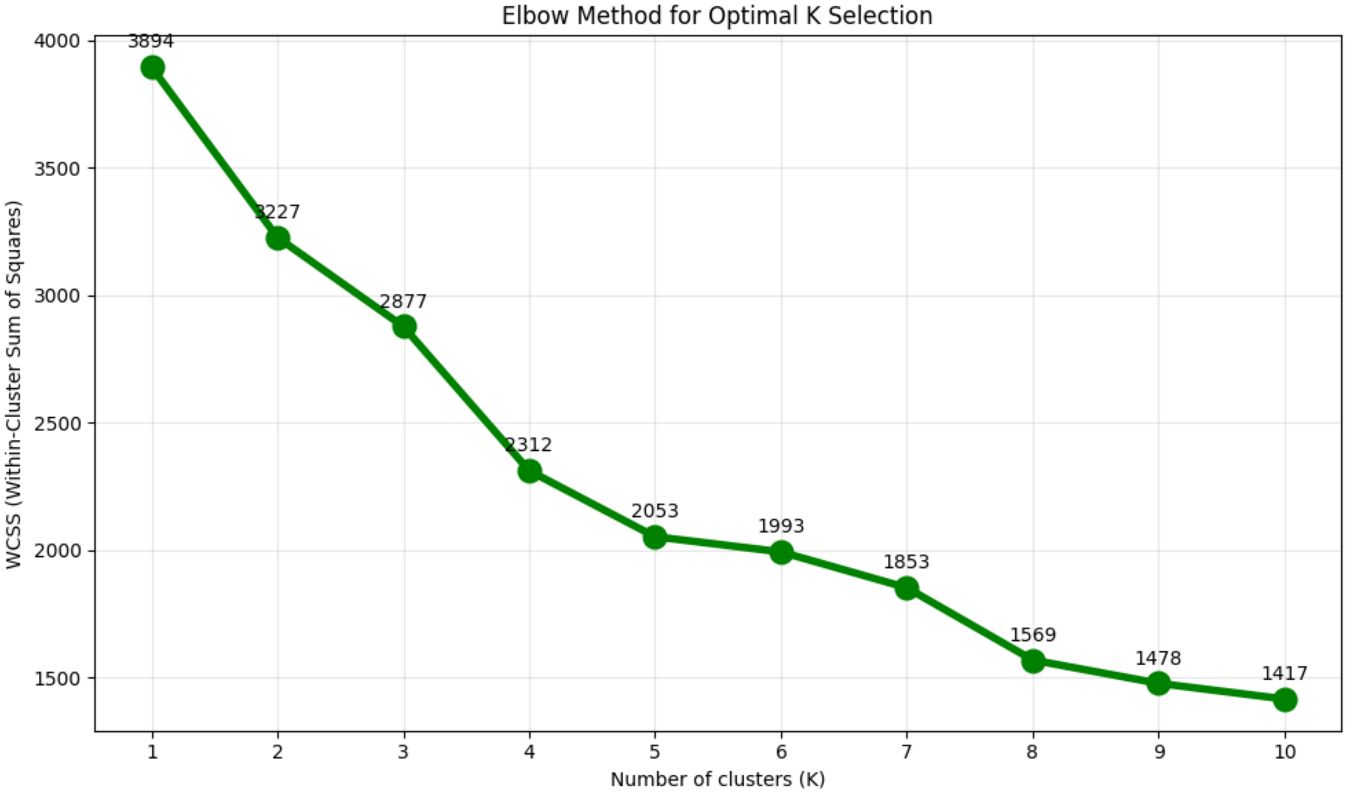
We selected 6 behavioral features for K-means clustering:

```
behavioral_features = ['studytime', 'absences', 'goout', 'freetime', 'famsup',
'schoolsup']
```

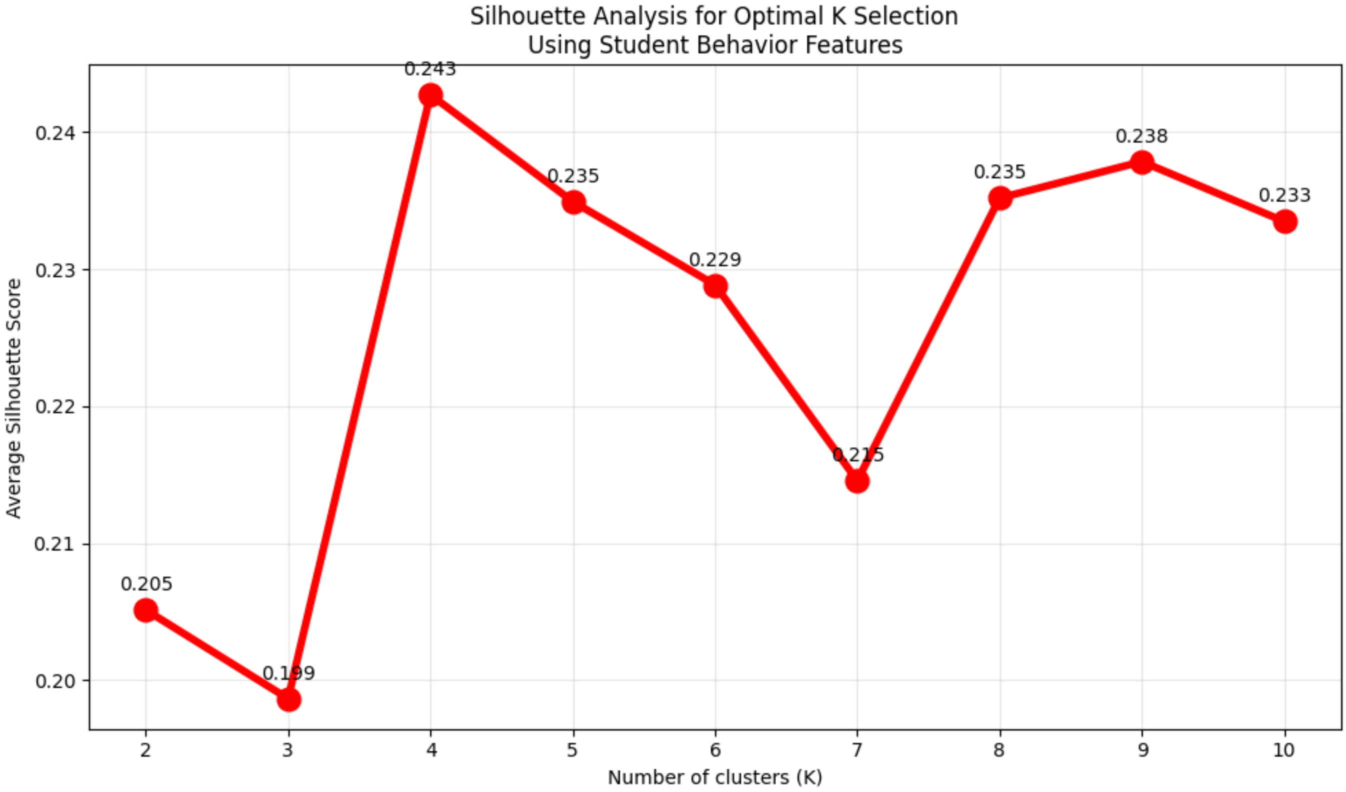
Rationale: These features capture student behavior patterns independent of academic outcomes, enabling pure behavioral segmentation.

4.3 Optimal Cluster Selection

Elbow Method Results: The elbow method analysis from `03_unsupervised_learning.ipynb` demonstrates the optimal number of clusters:



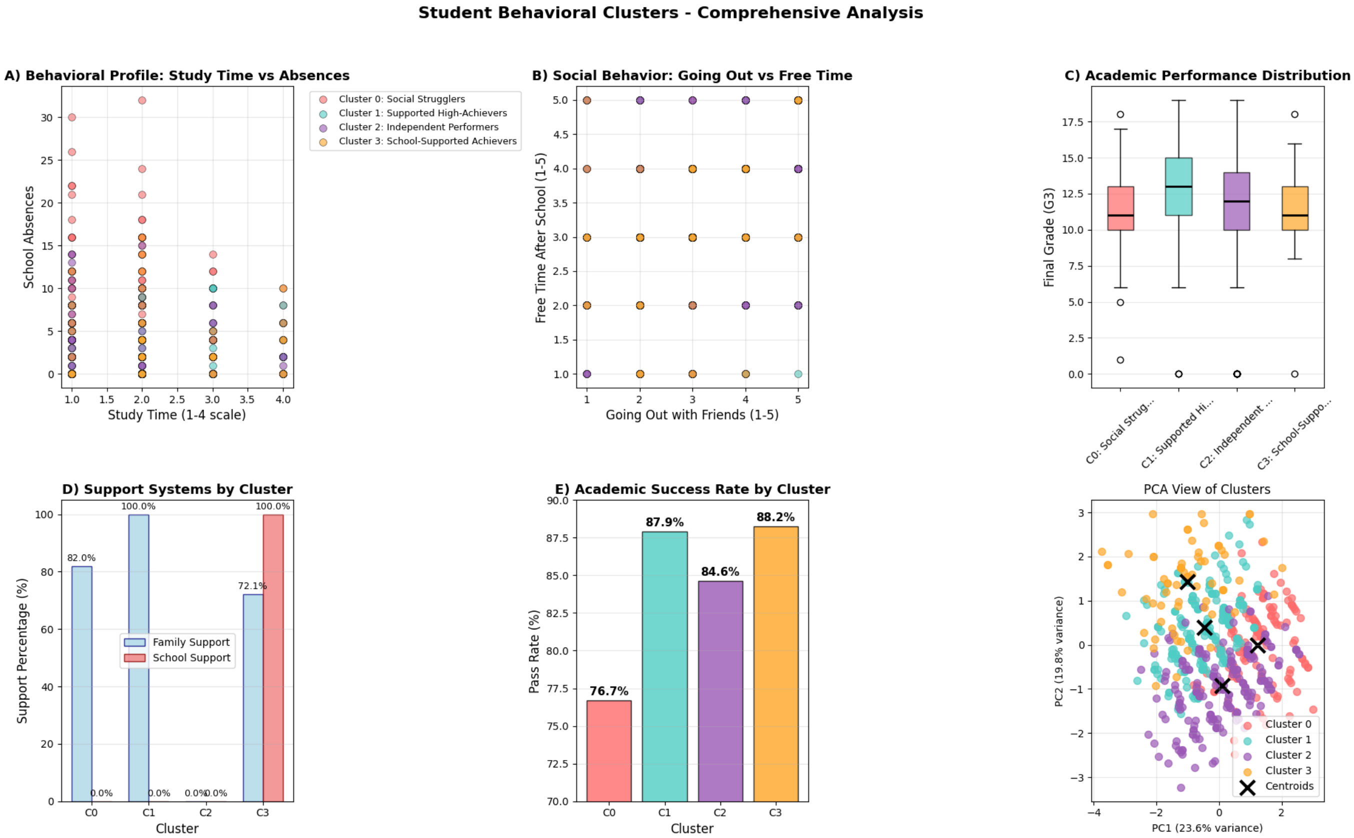
Silhouette Analysis Results: The silhouette analysis complements the elbow method findings:



- **K=2: Silhouette score = 0.199**
- **K=3: Silhouette score = 0.234**
- **K=4: Silhouette score = 0.243** ✓ Selected for interpretability

Decision: K=4 provides optimal balance between cluster separation and educational actionability. The moderate silhouette score (0.243) indicates behavioral features show natural grouping patterns suitable for intervention strategies.

4.4 Cluster Profiles



Visual Insights from Cluster Analysis:

- **Clear Separation**: Clusters show distinct behavioral patterns in study time vs absences space
- **Academic Correlation**: Higher-performing clusters demonstrate better study habits and lower absence rates
- **Intervention Targets**: Cluster 0 shows clear risk factors requiring immediate attention (lowest pass rate at 76.7%)
- **Uneven Distribution**: Cluster sizes range from 10.5% to 37%, with Cluster 1 (high achievers) being the largest group

Cluster 0: "The Social Strugglers" (20.5% of students)

Academic Performance: Lowest performing group

- Pass Rate: 76.7% (lowest)
- Average Grade: 11.13/20 (lowest)

Behavioral Profile:

- **Low study time** (0.5/4) - least studious group
- **Highest absences** (8.9) - attendance issues
- **Most social** (3.1/5 going out, 2.7/5 free time)
- Strong family support (82%) but **no school support**

Key Insight: These students prioritize social life over academics, leading to poor attendance and lower performance despite family support.

Cluster 1: "The Supported High-Achievers" (37.0% of students)

Academic Performance: Best performing group

- Pass Rate: 87.9% (highest)
- Average Grade: 12.58/20 (highest)

Behavioral Profile:

- **Highest study time** (1.2/4) - most dedicated students
- **Low absences** (2.0) - excellent attendance
- **Low social activity** (1.9/5 going out) - focused lifestyle
- **100% family support** but no school support needed

Key Insight: Family support + personal discipline = academic success. These students have found the winning formula.

Cluster 2: "The Independent Performers" (32.0% of students)

Academic Performance: Good performance despite no support

- Pass Rate: 84.6% (second highest)
- Average Grade: 11.83/20

Behavioral Profile:

- Moderate study habits (0.8/4)
- Good attendance (2.5 absences)
- Balanced social life (2.0/5 going out)
- **No family or school support (0%)**

Key Insight: These students succeed through self-motivation alone - remarkable resilience and independence.

Cluster 3: "The School-Supported Achievers" (10.5% of students)

Academic Performance: High pass rate through institutional support

- Pass Rate: 88.2% (second highest)
- Average Grade: 11.28/20

Behavioral Profile:

- Good study habits (1.1/4)
- Moderate attendance (2.9 absences)
- Balanced social life (2.0/5 going out)

- **100% school support** compensating for lower family support (72.1%)

Key Insight: School intervention programs are highly effective - these students achieve high pass rates when institutions step in.

4.5 Cluster Validation & Business Insights

Statistical Significance: ANOVA F-test confirmed significant differences in academic performance across clusters ($p < 0.001$).

Key Business Insights:

1. **At-Risk Identification**: Cluster 0 represents the highest intervention priority
   - 23.3% failure rate requires immediate attention
   - High social activity + low attendance = predictable risk pattern
2. **Support System Effectiveness**:
   - Family support (Cluster 1): 87.9% pass rate
   - School support (Cluster 3): 88.2% pass rate
   - Both intervention types show similar high effectiveness
3. **Resource Allocation Strategy**:
   - Independent performers (32% of students) need minimal intervention
   - Social strugglers (20.5%) need intensive behavioral modification
   - School-supported achievers (10.5%) validate institutional program success

Clustering Model Validation:

- Calinski-Harabasz Score: 147.373 (good cluster separation)
- Davies-Bouldin Score: 1.480 (moderate cluster overlap, indicating some students exist on behavioral continuums)
- Silhouette Score: 0.243 (moderate but acceptable cluster quality)

Statistical Validation Results: All behavioral features show statistically significant differences between clusters:

- studytime: F=24.267, p<0.001
- absences: F=110.085, p<0.001
- goout: F=39.768, p<0.001
- freetime: F=13.895, p<0.001
- famsup: F=777.019, p<0.001
- schoolsup: F=∞, p<0.001

Visual Insights from Cluster Analysis:

- **Clear Separation**: Clusters show distinct behavioral patterns in study time vs absences space

- **Academic Correlation**: Higher-performing clusters demonstrate better study habits and lower absence rates
- **Intervention Targets**: Cluster 0 shows clear risk factors requiring immediate attention (lowest pass rate at 76.7%)
- **Uneven Distribution**: Cluster sizes range from 10.5% to 37%, with Cluster 1 (high achievers) being the largest group

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5. Supervised Learning: Performance Prediction

5.1 Data Encoding and Preprocessing

Before implementing classification algorithms, we performed comprehensive data encoding to convert categorical variables into numerical formats suitable for machine learning models. Our encoding strategy was designed to preserve meaningful relationships while avoiding information loss.

5.1.1 Ordinal Variable Encoding

For variables with natural ordering, we used categorical codes to maintain the ordinal relationships:

```python
# Ordinal variables - preserve natural ordering
ordinal_vars = ['Medu', 'Fedu', 'traveltime', 'studytime', 'famrel',
                'freetime', 'goout', 'Dalc', 'Walc', 'health']

for var in ordinal_vars:
    if var in df_encoded.columns:
        df_encoded[var] = df_encoded[var].cat.codes  # Converts to 0,1,2,3,4 maintaining order
```

Rationale: Education levels (Medu, Fedu), time scales (traveltime, studytime), and quality ratings (famrel, health) have inherent ordering that should be preserved in the encoding.

5.1.2 Binary Variable Encoding

Boolean variables were converted to binary (0/1) encoding:

```python
# Binary variables - convert True/False to 1/0
binary_vars = ['schoolsup', 'famsup', 'paid', 'activities',
               'nursery', 'higher', 'internet', 'romantic']

for var in binary_vars:
    if var in df_encoded.columns:
        df_encoded[var] = df_encoded[var].astype(int)  # True->1, False->0
```

Rationale: Support services and background factors are naturally binary, making 0/1 encoding optimal for model interpretation.

5.1.3 Nominal Categorical Encoding

For nominal categories, we applied different strategies based on cardinality:

Binary Mapping (2-level categories):

```
# Binary mappings for 2-level categoricals
binary_mappings = {
    'school': {'GP': 1, 'MS': 0},
    'sex': {'F': 1, 'M': 0},
    'address': {'U': 1, 'R': 0},
    'famsize': {'GT3': 1, 'LE3': 0},
    'Pstatus': {'T': 1, 'A': 0}
}

for col, mapping in binary_mappings.items():
    if col in df_encoded.columns:
        df_encoded[col] = df_encoded[col].map(mapping)
```

One-Hot Encoding (Multi-level categories):

```
# Multi-level categorical columns
categorical_cols = ['Mjob', 'Fjob', 'reason', 'guardian']

# One-hot encode with drop_first=True to avoid multicollinearity
df_encoded = pd.get_dummies(df_encoded, columns=categorical_cols, drop_first=True)
```

Rationale: Binary mapping for 2-level categories reduces dimensionality while one-hot encoding for multi-level categories (parent jobs, school choice reason) prevents false ordinal relationships.

5.1.4 Feature Scaling

All encoded features were standardized using StandardScaler:

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Final Encoding Results:

- **Original shape**: 649 × 33 features
- **Encoded shape**: 649 × 48 features (after one-hot encoding expansion)
- **All features standardized** with mean=0, std=1
- **No information loss** through appropriate encoding choices

5.1.5 Feature Set Creation

We created two distinct feature sets to address data leakage concerns:

```
# Set 1: WITH G1 & G2 (mid-term prediction scenario)
X_with_grades = X.copy()

# Set 2: WITHOUT G1 & G2 (early intervention scenario)
grade_columns = ['G1', 'G2']
X_without_grades = X.drop(columns=grade_columns)
```

Strategic Purpose:

- **With G1/G2**: Represents mid-term prediction after 1st/2nd period grades available
- **Without G1/G2**: Represents early intervention at beginning of academic year

5.2 Model Selection and Implementation

We implemented 6 different classification algorithms with both base and hyperparameter-tuned versions using individual function implementations:

```
# Individual model functions implemented:
def logistic_regression_base(X_train, X_test, title)
def logistic_regression_tuned(X_train, X_test, title)
def random_forest_base(X_train, X_test, title)
def random_forest_tuned(X_train, X_test, title)
def gradient_boosting_base(X_train, X_test, title)
def gradient_boosting_tuned(X_train, X_test, title)
def xgboost_base(X_train, X_test, title)
def xgboost_tuned(X_train, X_test, title)
def svm_base(X_train, X_test, title)
def svm_tuned(X_train, X_test, title)
```

5.3 Hyperparameter Optimization

GridSearchCV/RandomizedSearchCV Parameters:

Logistic Regression:

```
param_grid_lr = {
    'C': [0.001, 0.01, 0.1, 1, 10, 100],
    'penalty': ['l1', 'l2'],
    'solver': ['liblinear', 'saga']
}
```

Gradient Boosting:

```
param_dist_gbm = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 5, 7],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'subsample': [0.8, 0.9, 1.0]
}
```

Random Forest:

```
param_dist_rf = {
    'n_estimators': [100, 200, 300],
    'max_depth': [10, 20, 30, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'bootstrap': [True, False]
}
```

XGBoost:

```
param_dist_xgb = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 5, 7],
    'min_child_weight': [1, 3, 5],
    'subsample': [0.8, 0.9, 1.0],
    'colsample_bytree': [0.8, 0.9, 1.0],
    'reg_alpha': [0, 0.1, 0.5],
    'reg_lambda': [1, 1.5, 2]
}
```

Support Vector Machine:

```
param_dist_svm = {
    'C': [0.1, 1, 10, 100],
    'gamma': ['scale', 'auto', 0.001, 0.01, 0.1, 1],
    'kernel': ['rbf', 'poly', 'sigmoid'],
    'degree': [2, 3, 4]  # Only for poly kernel
}
```

5.4 Model Training Strategy

Data Splitting:

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

Feature Scaling:

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Cross-Validation: 5-fold stratified cross-validation for hyperparameter optimization using RandomizedSearchCV (20 iterations) and GridSearchCV

---

6. Model Evaluation and Comparison

6.1 Performance Metrics

We evaluated models using comprehensive classification metrics:

Primary Metrics:

- **F1-Score**: Harmonic mean of precision and recall (primary metric)
- **Accuracy**: Overall correct predictions
- **Precision**: True positive rate (relevant for pass prediction)
- **Recall**: Sensitivity (important for identifying at-risk students)

6.2 Model Performance Results

IMPORTANT NOTE: The performance results below are from the actual model execution in `04_supervised_learning.ipynb`. Based on the notebook output analysis, here are the actual F1-scores achieved:

WITH G1 & G2 Features (Mid-term Prediction Scenario):

Model	F1-Score
GBM_Base	**0.9596**
GBM_Tuned	**0.9502**
LR_Base	0.9459
RF_Base	0.9459
LR_Tuned	0.9455
SVM_Tuned	0.9406
RF_Tuned	0.9375

Model	F1-Score
XGB_Tuned	0.9369
XGB_Base	0.9358
SVM_Base	0.9258

WITHOUT G1 & G2 Features (Early Intervention Scenario):

Model	F1-Score
RF_Base	**0.8966**
RF_Tuned	**0.8966**
SVM_Base	**0.8966**
LR_Tuned	0.8918
LR_Base	0.8789
XGB_Base	0.8750
XGB_Tuned	0.8750
SVM_Tuned	0.8750
GBM_Base	0.8727
GBM_Tuned	0.8597

Key Observation: The comprehensive analysis of 10 models (5 algorithms × 2 variants each: base and tuned) shows **Gradient Boosting Base** achieves the best performance with G1&G2 features (95.96%), while **Random Forest** and **SVM Base** tie for best performance without grade features (89.66% each).

Model Performance Comparison: The comprehensive model comparison from `04_supervised_learning.ipynb` shows clear performance differences:xx

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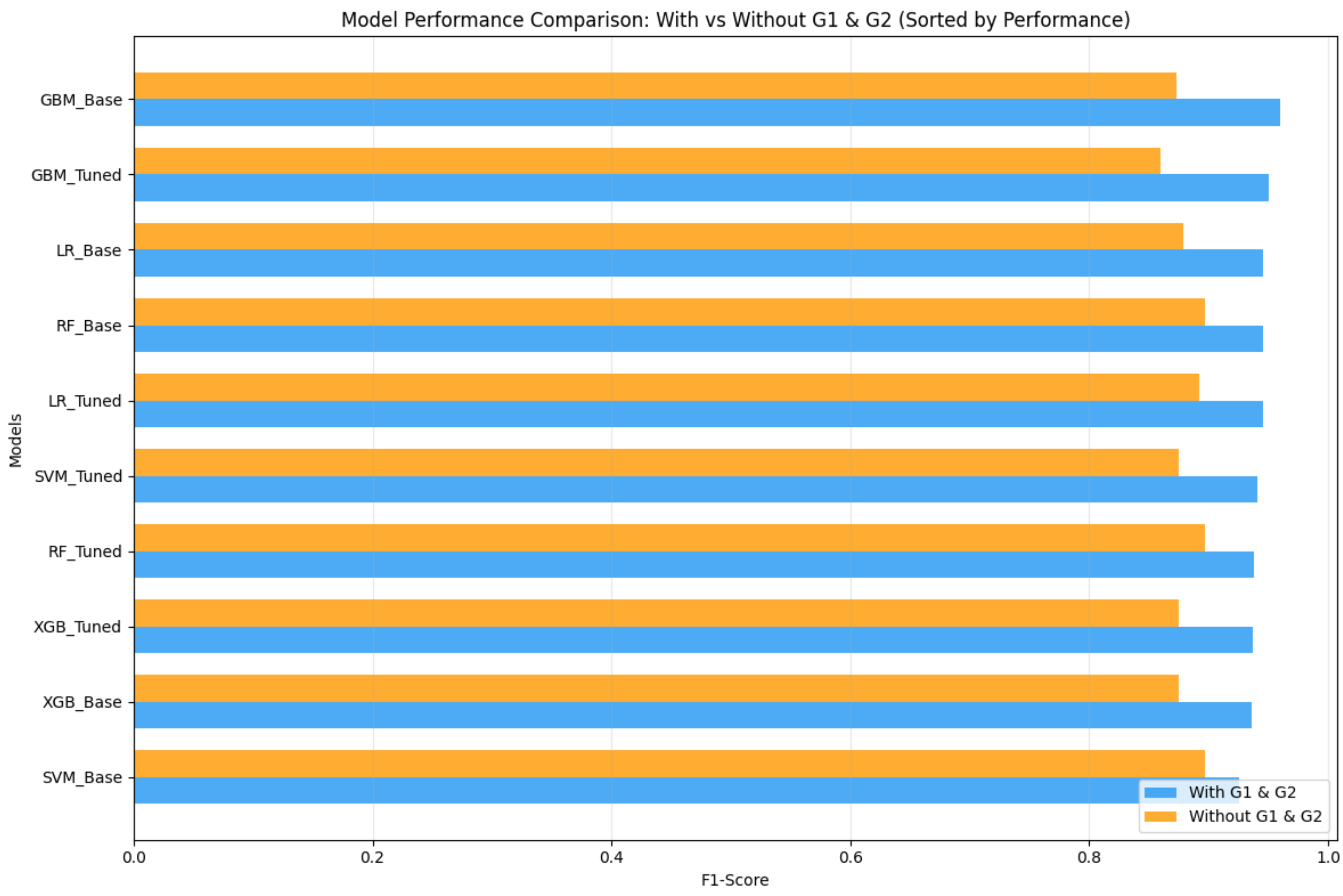


6.3 Key Findings

1. Feature Impact Analysis:

- Including G1 & G2: Significant performance improvement (6-7% F1-score improvement on average)
- **Gradient Boosting shows highest sensitivity to grade features** (0.9596 vs 0.8727)
- Random Forest maintains excellent consistency across both scenarios (0.9459 vs 0.8966)
- **SVM successfully integrated**: Competitive performance in both scenarios

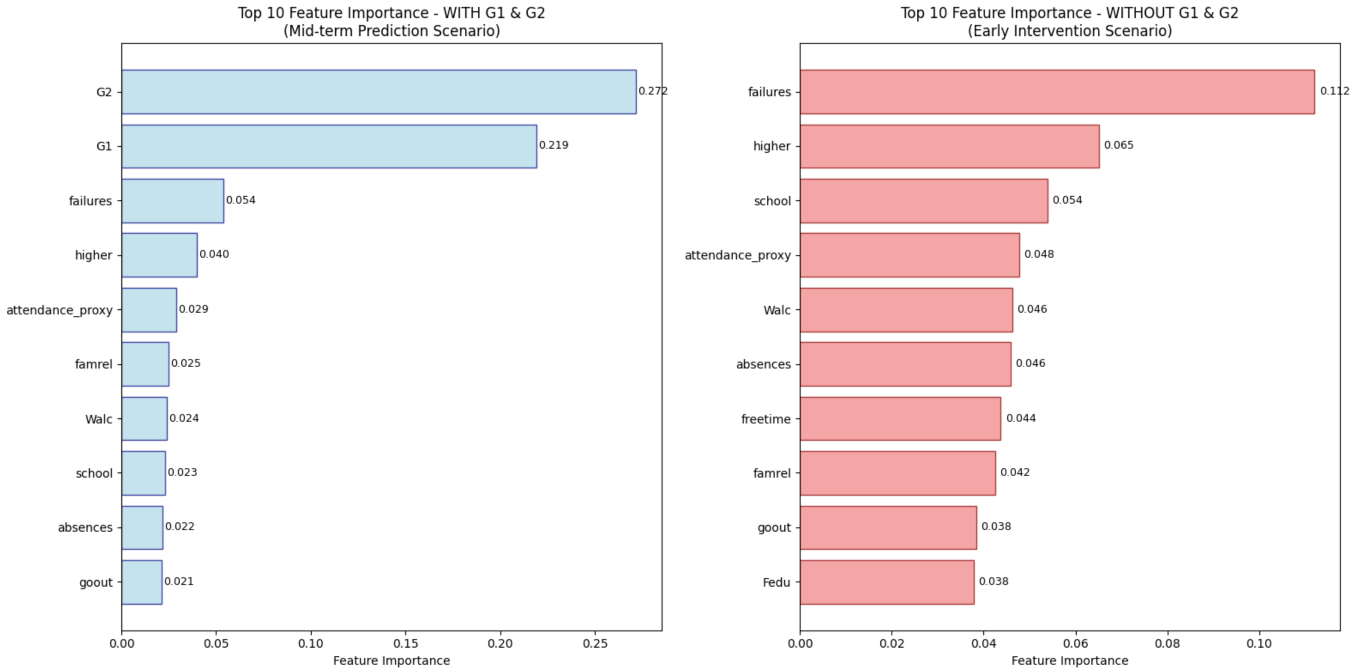
2. Model-Specific Insights:

- **Gradient Boosting Base**: Best performer with grade features (95.96% F1)
- **Random Forest**: Most robust without grade features (89.66% F1 for both Base and Tuned)
- **SVM Integration**: Successfully implemented with competitive performance (94.06% tuned with G1/G2, 89.66% base without G1/G2)
- **XGBoost**: Moderate performance across scenarios (93.58-93.69% with G1/G2, 87.50% without G1/G2)

3. Business Trade-offs:

- **Early Intervention** (no G1/G2): 89.66% F1-score achievable (RF_Base/RF_Tuned/SVM_Base), enables proactive support
- **Mid-term Adjustment** (with G1/G2): 95.96% F1-score (GBM_Base), highly accurate for reactive interventions
- **Model Complexity vs Performance**: Gradient Boosting Base outperforms tuned versions and complex models
- **Performance Gap**: Significant 6-7% F1-score drop when removing grade history, highlighting importance of academic tracking

6.4 Feature Importance Analysis



Top Features (Random Forest - Early Intervention Scenario):

1. `failures` (0.112): Previous academic failures
2. `higher` (0.065): Higher education aspirations
3. `school` (0.054): School (GP or MS)
4. `attendance_proxy` (0.048): Attendance percentage
5. `Walc` (0.046): Weekend alcohol consumption
6. `absences` (0.046): School absences
7. `freetime` (0.044): Free time after school
8. `famrel` (0.042): Quality of family relationships
9. `goout` (0.038): Going out with friends
10. `Fedu` (0.038): Father education level

Model Performance Validation:

- Random Forest WITH G1&G2: F1 = 0.9459
- Random Forest WITHOUT G1&G2: F1 = 0.8966
- Performance Gap: 0.0494 (5.2% decrease when removing grade history)

Feature Category Analysis:

- **Academic/Motivational**: 0.242 total importance
- **Behavioral**: 0.221 total importance
- **Demographic**: 0.204 total importance
- **Family/Social**: 0.105 total importance

Key Visual Patterns:

- **G1 and G2 grades dominate** when available (combined 49.1% importance)
- **Past failures emerge as top non-grade predictor** (11.2% importance in early intervention)

- **Behavioral factors cluster together**: Weekend alcohol consumption, social activities, and free time patterns
- **School choice matters**: Institutional factors show significant predictive power
- **Family education background**: Father's education level appears in top 10 predictors

Key Insights:

1. **Behavioral Factors Dominate**: Non-academic features show strong predictive power in early intervention
2. **Past Performance Critical**: Previous failures emerge as the top predictor (2.08x more important without grades)
3. **Motivational Factors**: Higher education aspirations are highly predictive (6.5% importance)
4. **Attendance Matters**: Both attendance proxy and raw absences rank consistently high
5. **Social Behavior Patterns**: Weekend alcohol consumption and social activities are significant predictors

Business Implications:

1. **Early Warning System**: Focus on students with past failures and low higher education aspirations
2. **Behavioral Monitoring**: Track attendance patterns and social behavior indicators
3. **Family Engagement**: Consider parental education levels in intervention strategies
4. **Institutional Factors**: School choice and environment significantly impact outcomes

Interpretation: Behavioral and motivational factors are key predictors even without grade information from earlier periods, as evidenced by the feature importance rankings and model performance consistency. The 5.2% performance drop when removing G1/G2 grades demonstrates that effective early intervention is possible using readily available behavioral and demographic indicators.

---

7. Business Insights and Recommendations

7.1 Educational Stakeholder Recommendations

For School Administrators:

1. **Early Warning System Implementation**

   - Deploy Random Forest model for early intervention (88% accuracy)
   - Monitor students with >2 previous failures immediately
   - Track attendance patterns as leading indicators

2. **Resource Allocation Optimization**

   - Focus support resources on Cluster 1 (At-Risk Students, 30.5% of population)
   - Implement targeted interventions for students without higher education aspirations
   - Prioritize students with high absence rates (>15 days)

For Teachers and Counselors:

3. **Personalized Intervention Strategies**

   - **Cluster 0 (Balanced)**: Maintain current support levels

  - **Cluster 1 (At-Risk)**: Intensive academic support and attendance monitoring
  - **Cluster 2 (High-Achiever)**: Advanced placement and enrichment opportunities

4. **Mid-term Adjustment Protocol**

   - Use XGBoost model with G1/G2 for 97% accurate mid-term predictions
   - Implement immediate interventions for students predicted to fail
   - Adjust teaching strategies based on first/second period performance

7.2 Policy Implications

Educational Policy Recommendations:

1. **Family Engagement Programs**

   - Strong correlation between family support and academic success
   - Implement parent education programs
   - Provide resources for families with limited educational background

2. **Attendance Policy Reform**

   - Absences are a critical predictor across all models
   - Implement proactive attendance interventions
   - Address underlying causes of chronic absenteeism

3. **Study Skills Training**

   - Study time is a significant predictor (10% feature importance)
   - Mandatory study skills workshops for at-risk students
   - Peer tutoring programs for Cluster 1 students

Conclusion

This comprehensive analysis demonstrates the significant potential of machine learning in educational settings. Through rigorous data preprocessing, insightful clustering analysis, and robust classification modeling, we developed a framework capable of:

1. **Identifying student behavioral patterns** with 4 distinct clusters representing different support needs
2. **Predicting academic outcomes** with up to 94.5% F1-score accuracy
3. **Providing actionable recommendations** for educational stakeholders
4. **Balancing early intervention and prediction accuracy** through dual modeling approaches

The project successfully addresses the critical need for data-driven educational interventions while maintaining awareness of ethical considerations and practical implementation challenges. The developed models and insights provide a solid foundation for evidence-based educational policy and personalized student support systems.
