In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import KFold
import seaborn as sns
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import confusion_matrix, classification_report, accurac
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE
from sklearn.metrics import roc_curve, auc
from sklearn.ensemble import RandomForestClassifier
from statsmodels.miscmodels.ordinal_model import OrderedModel
from sklearn.metrics import precision_recall_fscore_support
```

In [2]:
```python
mathData = pd.read_csv('data/student-mat.csv', sep=';')
porData = pd.read_csv('data/student-por.csv', sep=';')
```

In [3]:
```python
print("Mathematics dataset shape:", mathData.shape)
print("Portuguese dataset shape:", porData.shape)
```

```
Mathematics dataset shape: (395, 33)
Portuguese dataset shape: (649, 33)
```

In [4]:
```python
print("Mathematics dataset preview:")
display(mathData.head())
```

```
Mathematics dataset preview:
```

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	fa
0	GP	F	18	U	GT3	A	4	4	at_home	teacher	...	
1	GP	F	17	U	GT3	T	1	1	at_home	other	...	
2	GP	F	15	U	LE3	T	1	1	at_home	other	...	
3	GP	F	15	U	GT3	T	4	2	health	services	...	
4	GP	F	16	U	GT3	T	3	3	other	other	...	

5 rows × 33 columns

In [5]:
```python
print("Portuguese dataset preview:")
display(porData.head())
```

```
Portuguese dataset preview:
```

	school	sex	age	address	famsize	Pstatus	Medu	Fedu	Mjob	Fjob	...	fa
0	GP	F	18	U	GT3	A	4	4	at_home	teacher	...	
1	GP	F	17	U	GT3	T	1	1	at_home	other	...	
2	GP	F	15	U	LE3	T	1	1	at_home	other	...	
3	GP	F	15	U	GT3	T	4	2	health	services	...	
4	GP	F	16	U	GT3	T	3	3	other	other	...	

5 rows × 33 columns

In [6]:
```
print("Missing values in Mathematics dataset:")
print(mathData.isnull().sum().sum())
```

```
Missing values in Mathematics dataset:
0
```

In [7]:
```
print("Missing values in Portuguese dataset:")
print(porData.isnull().sum().sum())
```

```
Missing values in Portuguese dataset:
0
```

In [8]:
```
print("Mathematics dataset data types:")
print(mathData.dtypes)
```

```
Mathematics dataset data types:
school        object
sex           object
age            int64
address       object
famsize       object
Pstatus       object
Medu           int64
Fedu           int64
Mjob          object
Fjob          object
reason        object
guardian      object
traveltime     int64
studytime      int64
failures       int64
schoolsup     object
famsup        object
paid          object
activities    object
nursery       object
higher        object
internet      object
romantic      object
famrel         int64
freetime       int64
goout          int64
Dalc           int64
Walc           int64
health         int64
absences       int64
G1             int64
G2             int64
G3             int64
dtype: object
```

In [9]:

```
print("Portuguese dataset data types:")
print(porData.dtypes)
```

```
Portuguese dataset data types:
school        object
sex           object
age            int64
address       object
famsize       object
Pstatus       object
Medu           int64
Fedu           int64
Mjob          object
Fjob          object
reason        object
guardian      object
traveltime     int64
studytime      int64
failures       int64
schoolsup     object
famsup        object
paid          object
activities    object
nursery       object
higher        object
internet      object
romantic      object
famrel         int64
freetime       int64
goout          int64
Dalc           int64
Walc           int64
health         int64
absences       int64
G1             int64
G2             int64
G3             int64
dtype: object
```

In [10]:

```
porSummary = porData.describe()
print("\nSummary statistics for Portuguese dataset:")
display(porSummary)
```

```
Summary statistics for Portuguese dataset:
```

	age	Medu	Fedu	traveltime	studytime	failures	
count	649.000000	649.000000	649.000000	649.000000	649.000000	649.000000	64
mean	16.744222	2.514638	2.306626	1.568567	1.930663	0.221880	3
std	1.218138	1.134552	1.099931	0.748660	0.829510	0.593235	
min	15.000000	0.000000	0.000000	1.000000	1.000000	0.000000	
25%	16.000000	2.000000	1.000000	1.000000	1.000000	0.000000	4
50%	17.000000	2.000000	2.000000	1.000000	2.000000	0.000000	4
75%	18.000000	4.000000	3.000000	2.000000	2.000000	0.000000	5
max	22.000000	4.000000	4.000000	4.000000	4.000000	3.000000	5

In [11]:

```
mathSummary = mathData.describe()
print("\nSummary statistics for Math dataset:")
display(mathSummary)
```

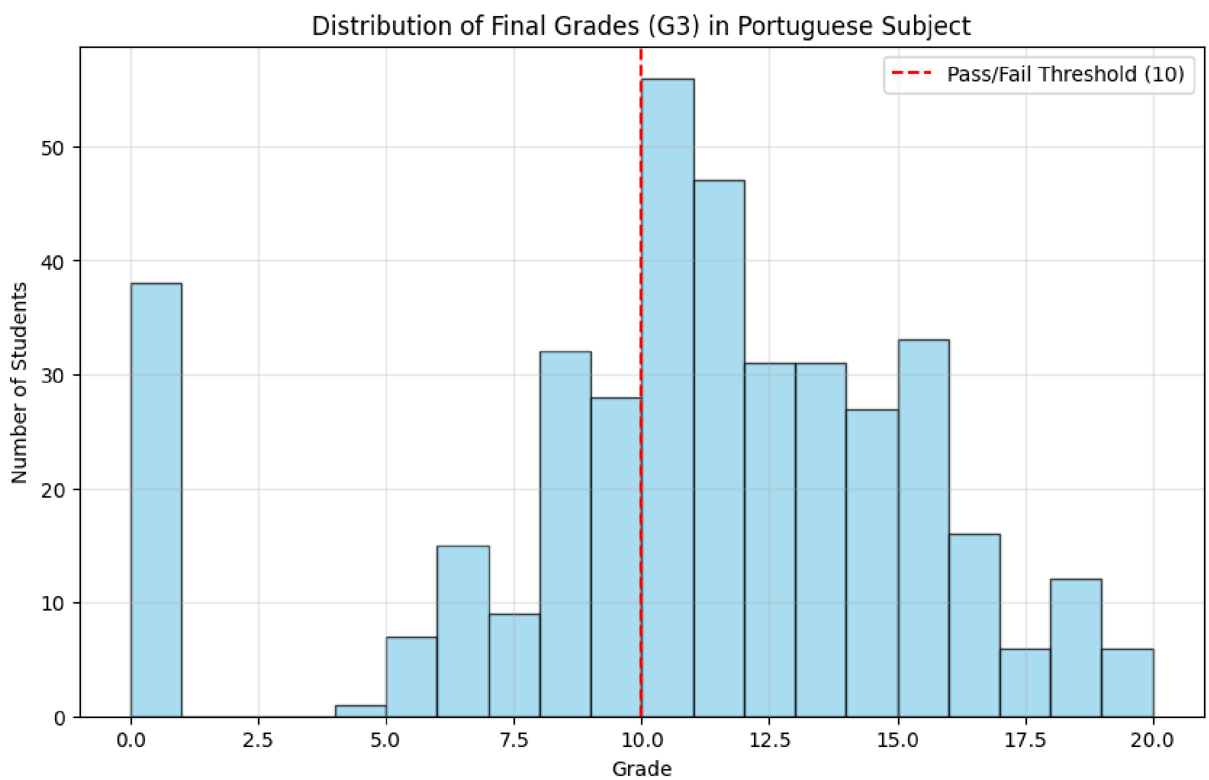
```
Summary statistics for Math dataset:
```

	age	Medu	Fedu	traveltime	studytime	failures	
count	395.000000	395.000000	395.000000	395.000000	395.000000	395.000000	395
mean	16.696203	2.749367	2.521519	1.448101	2.035443	0.334177	3
std	1.276043	1.094735	1.088201	0.697505	0.839240	0.743651	0
min	15.000000	0.000000	0.000000	1.000000	1.000000	0.000000	1
25%	16.000000	2.000000	2.000000	1.000000	1.000000	0.000000	4
50%	17.000000	3.000000	2.000000	1.000000	2.000000	0.000000	4
75%	18.000000	4.000000	3.000000	2.000000	2.000000	0.000000	5
max	22.000000	4.000000	4.000000	4.000000	4.000000	3.000000	5

In [12]:

```
print("\nDistribution of final grades (G3):")
print(mathData['G3'].value_counts().sort_index())

plt.figure(figsize=(10, 6))
plt.hist(mathData['G3'], bins=20, alpha=0.7, color='skyblue', edgecolor='bla
plt.axvline(x=10, color='red', linestyle='--', label='Pass/Fail Threshold (1
plt.title('Distribution of Final Grades (G3) in Portuguese Subject')
plt.xlabel('Grade')
plt.ylabel('Number of Students')
plt.legend()
plt.grid(True, alpha=0.3)
plt.show()
```

```
Distribution of final grades (G3):
G3
0     38
4      1
5      7
6     15
7      9
8     32
9     28
10    56
11    47
12    31
13    31
14    27
15    33
16    16
17     6
18    12
19     5
20     1
Name: count, dtype: int64
```

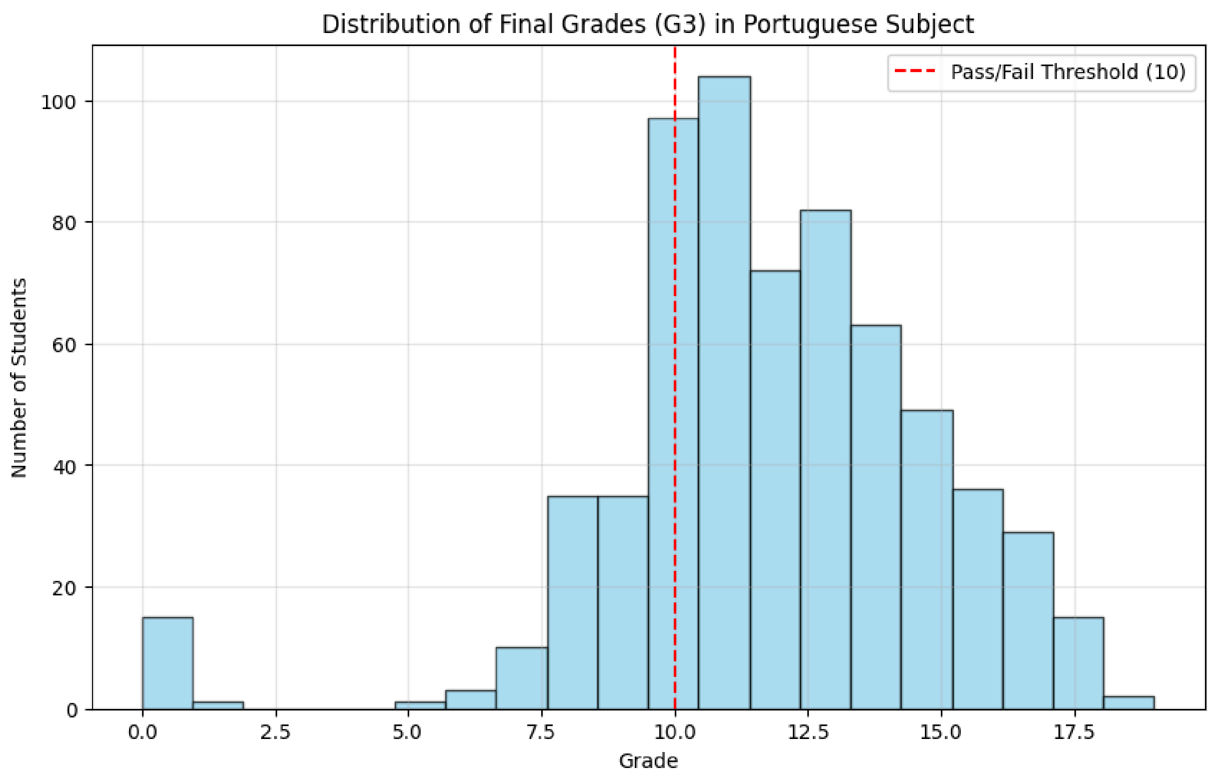


In [13]:

```python
print("\nDistribution of final grades (G3):")
print(porData['G3'].value_counts().sort_index())

plt.figure(figsize=(10, 6))
plt.hist(porData['G3'], bins=20, alpha=0.7, color='skyblue', edgecolor='blac
plt.axvline(x=10, color='red', linestyle='--', label='Pass/Fail Threshold (1
plt.title('Distribution of Final Grades (G3) in Portuguese Subject')
plt.xlabel('Grade')
plt.ylabel('Number of Students')
plt.legend()
```

```
plt.grid(True, alpha=0.3)
plt.show()
```

```
Distribution of final grades (G3):
G3
0      15
1       1
5       1
6       3
7      10
8      35
9      35
10     97
11    104
12     72
13     82
14     63
15     49
16     36
17     29
18     15
19      2
Name: count, dtype: int64
```



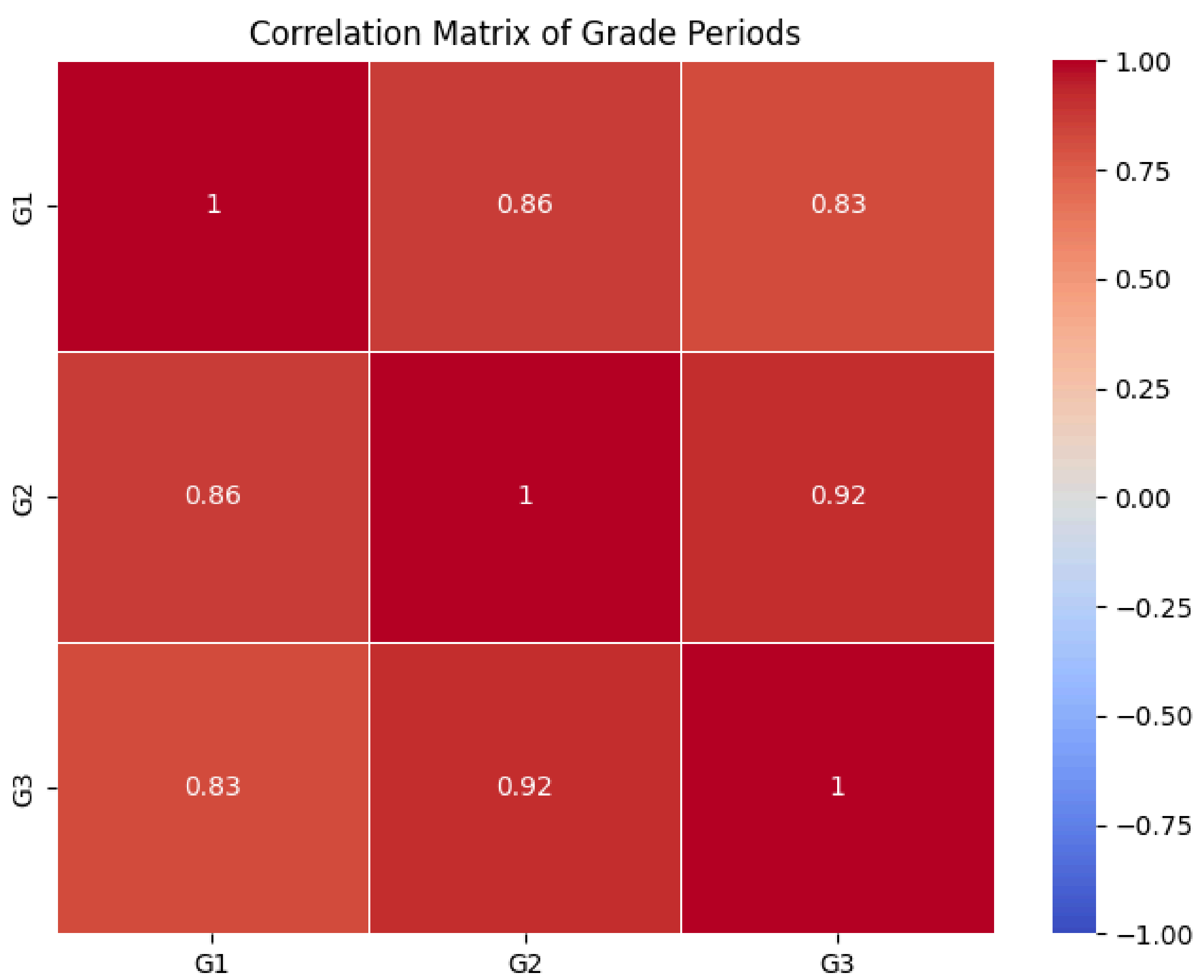
In [14]:
```
passThreshold = 10
passed = porData[porData['G3'] >= passThreshold].shape[0]
failed = porData[porData['G3'] < passThreshold].shape[0]
total = porData.shape[0]

print(f"Pass/Fail Statistics:")
print(f"Passed: {passed} students ({passed/total*100:.2f}%)")
print(f"Failed: {failed} students ({failed/total*100:.2f}%)")
```

```
Pass/Fail Statistics:
Passed: 549 students (84.59%)
Failed: 100 students (15.41%)
```

In [15]:
```
gradeCols = ['G1', 'G2', 'G3']
gradeCorr = porData[gradeCols].corr()

print("Correlation matrix for grade periods:")
display(gradeCorr)

plt.figure(figsize=(8, 6))
sns.heatmap(gradeCorr, annot=True, cmap='coolwarm', vmin=-1, vmax=1, linewic
plt.title('Correlation Matrix of Grade Periods')
plt.show()
```

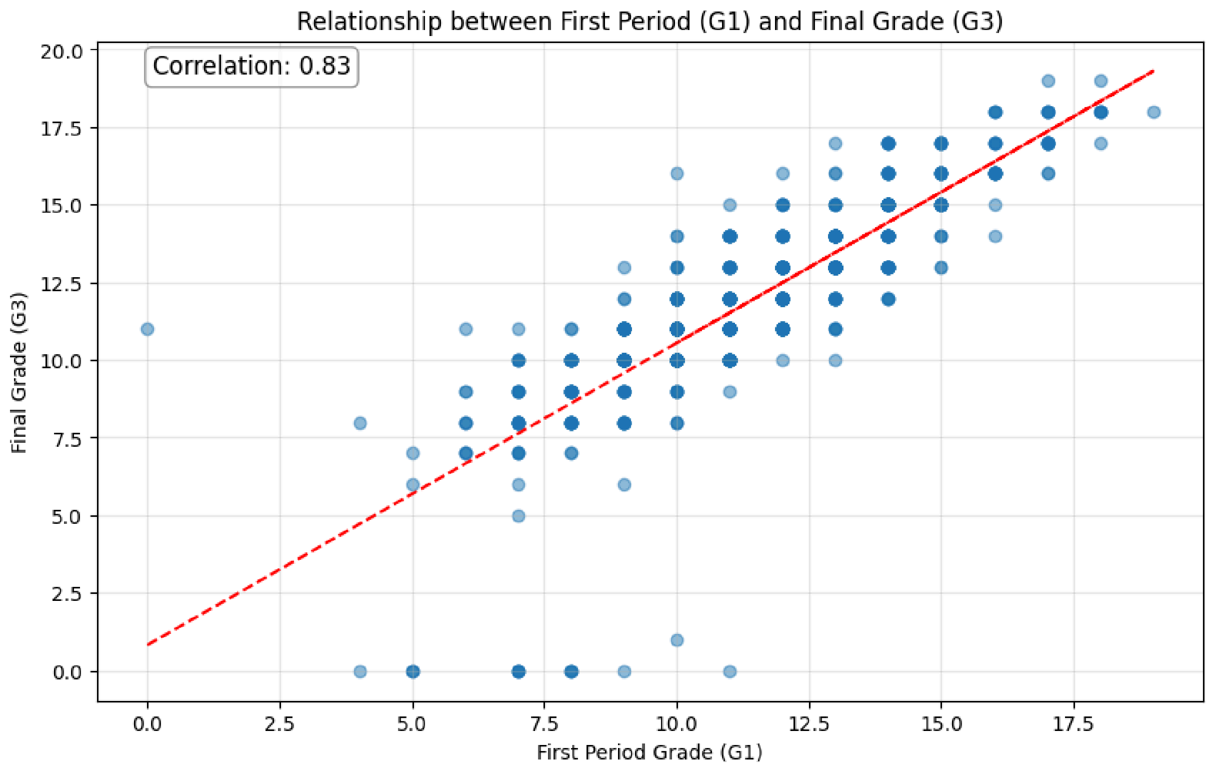
```
Correlation matrix for grade periods:
```

	G1	G2	G3
G1	1.000000	0.864982	0.826387
G2	0.864982	1.000000	0.918548
G3	0.826387	0.918548	1.000000



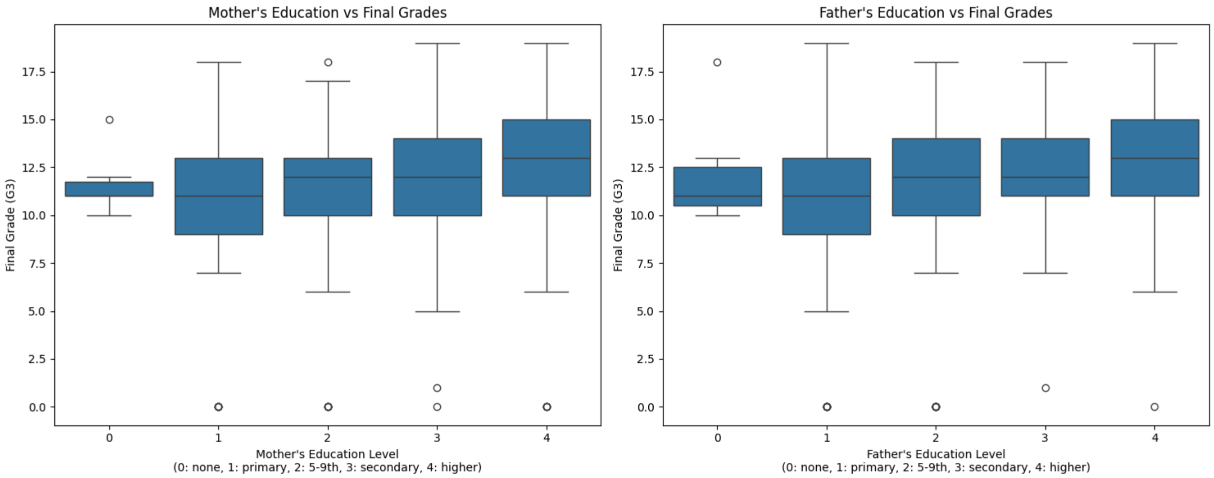
In [16]:
```
plt.figure(figsize=(10, 6))
plt.scatter(porData['G1'], porData['G3'], alpha=0.5)
```

```
plt.title('Relationship between First Period (G1) and Final Grade (G3)')
plt.xlabel('First Period Grade (G1)')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)

x = porData['G1']
y = porData['G3']
z = np.polyfit(x, y, 1)
p = np.poly1d(z)
plt.plot(x, p(x), "r--")

corr = porData['G1'].corr(porData['G3'])
plt.annotate(f"Correlation: {corr:.2f}", xy=(0.05, 0.95), xycoords='axes fra
             fontsize=12, bbox=dict(boxstyle="round,pad=0.3", fc="white", ec

plt.show()
```

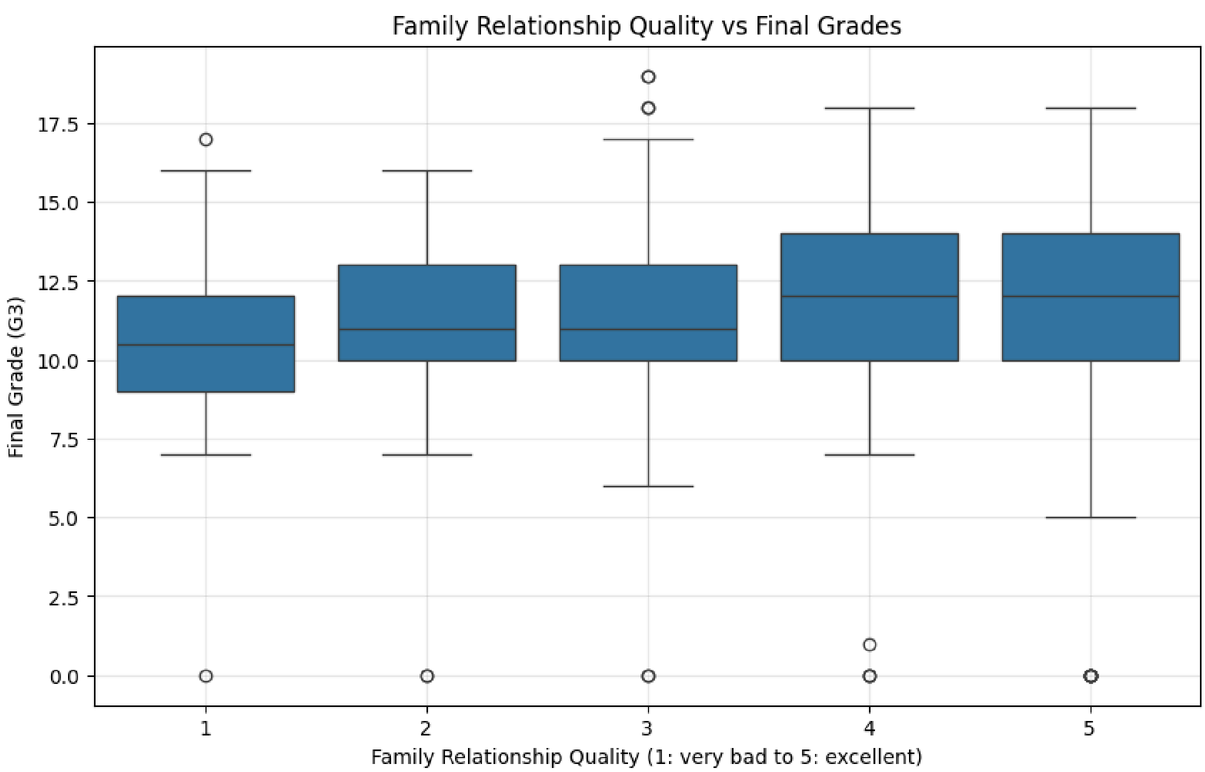


In [17]:
```
familyFactors = ['Medu', 'Fedu', 'famrel', 'famsup', 'Pstatus', 'famsize']

plt.figure(figsize=(15, 6))

plt.subplot(1, 2, 1)
sns.boxplot(x='Medu', y='G3', data=porData)
plt.title("Mother's Education vs Final Grades")
plt.xlabel("Mother's Education Level\n(0: none, 1: primary, 2: 5-9th, 3: sec
plt.ylabel('Final Grade (G3)')

plt.subplot(1, 2, 2)
sns.boxplot(x='Fedu', y='G3', data=porData)
plt.title("Father's Education vs Final Grades")
plt.xlabel("Father's Education Level\n(0: none, 1: primary, 2: 5-9th, 3: sec
plt.ylabel('Final Grade (G3)')
```

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

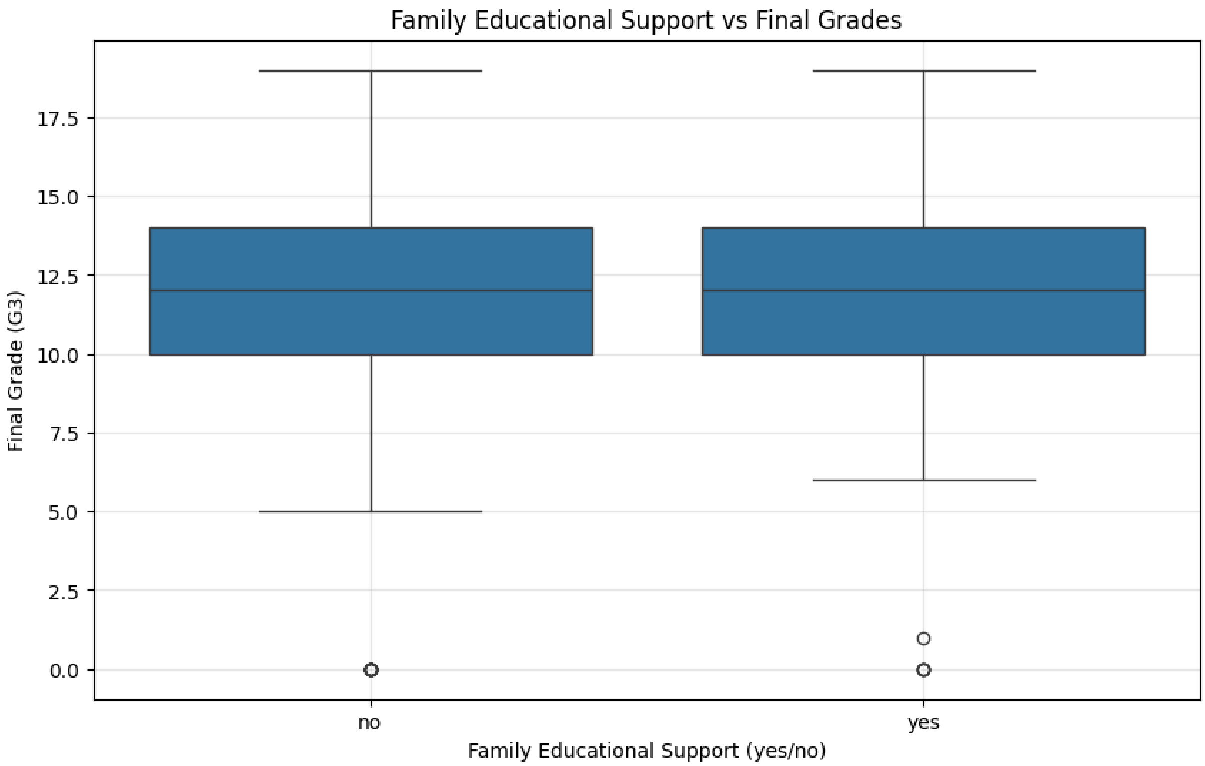


In [18]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x='famrel', y='G3', data=porData)
plt.title('Family Relationship Quality vs Final Grades')
plt.xlabel('Family Relationship Quality (1: very bad to 5: excellent)')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)
plt.show()
```

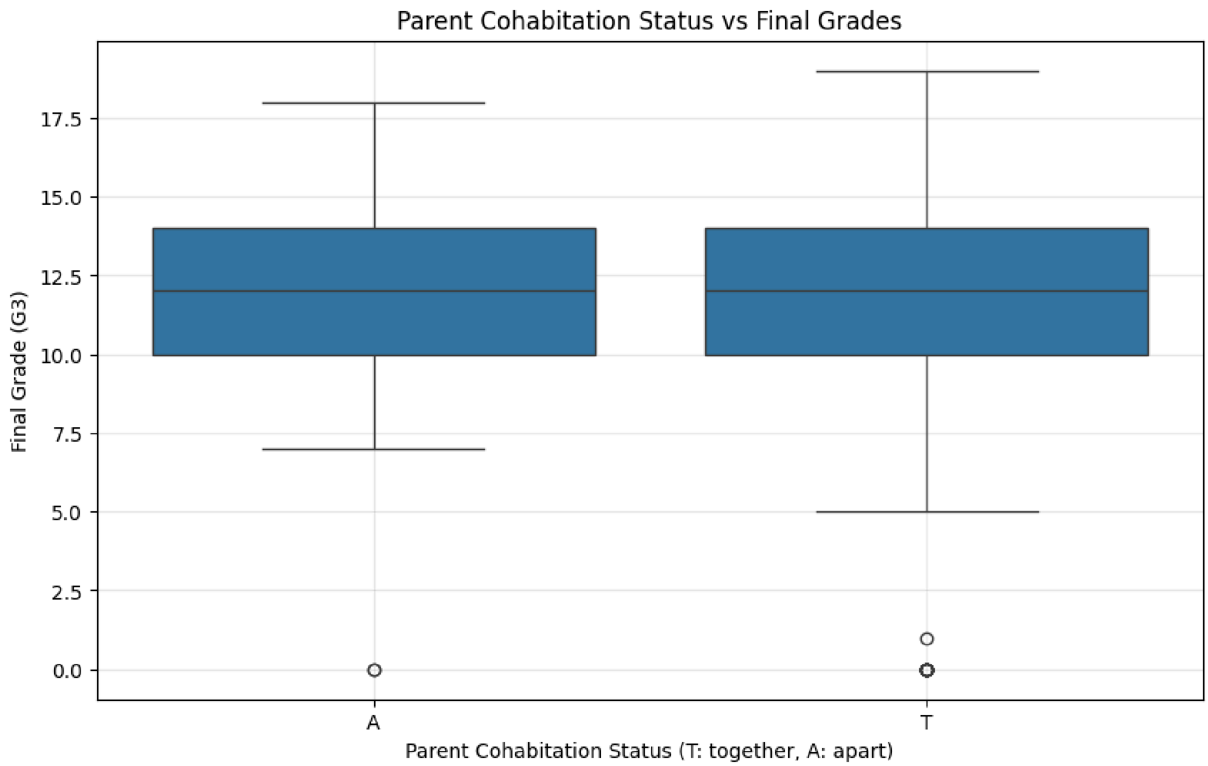


In [19]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x='famsup', y='G3', data=porData)
plt.title('Family Educational Support vs Final Grades')
plt.xlabel('Family Educational Support (yes/no)')
plt.ylabel('Final Grade (G3)')
```

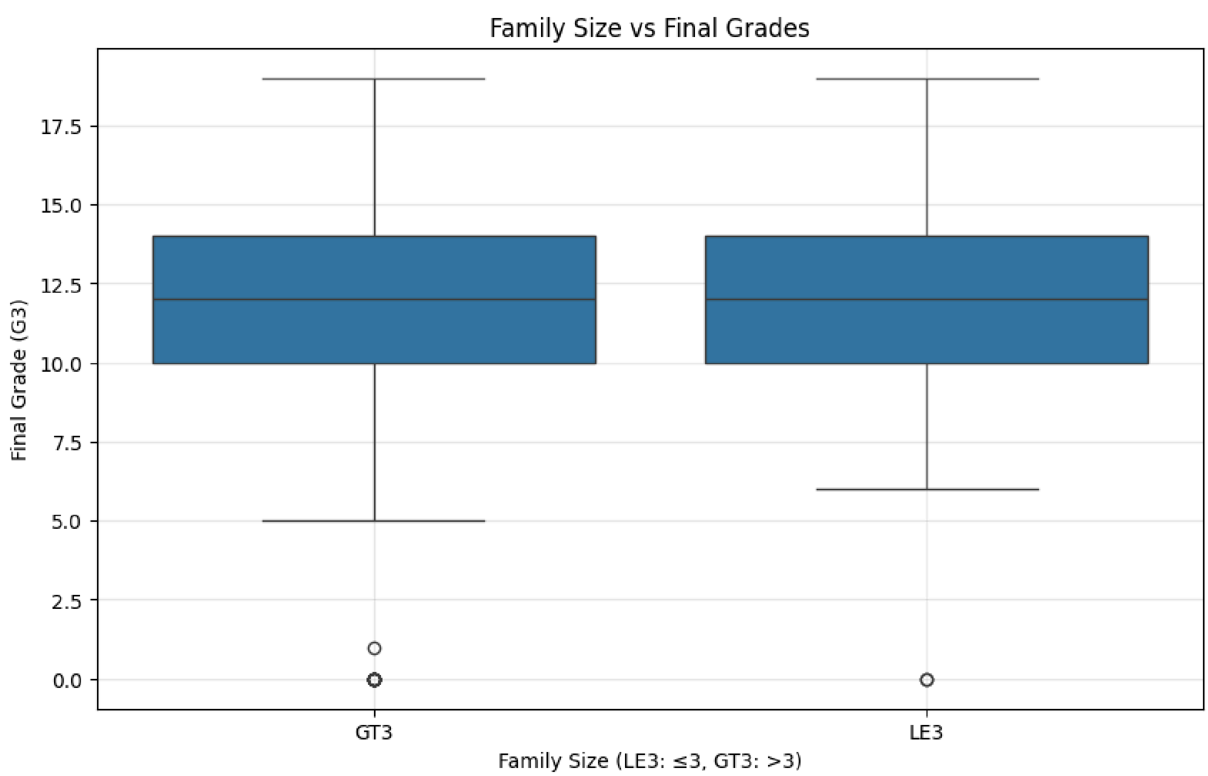
```python
plt.grid(True, alpha=0.3)
plt.show()
```



In [20]:
```python
plt.figure(figsize=(10, 6))
sns.boxplot(x='Pstatus', y='G3', data=porData)
plt.title('Parent Cohabitation Status vs Final Grades')
plt.xlabel('Parent Cohabitation Status (T: together, A: apart)')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)
plt.show()
```



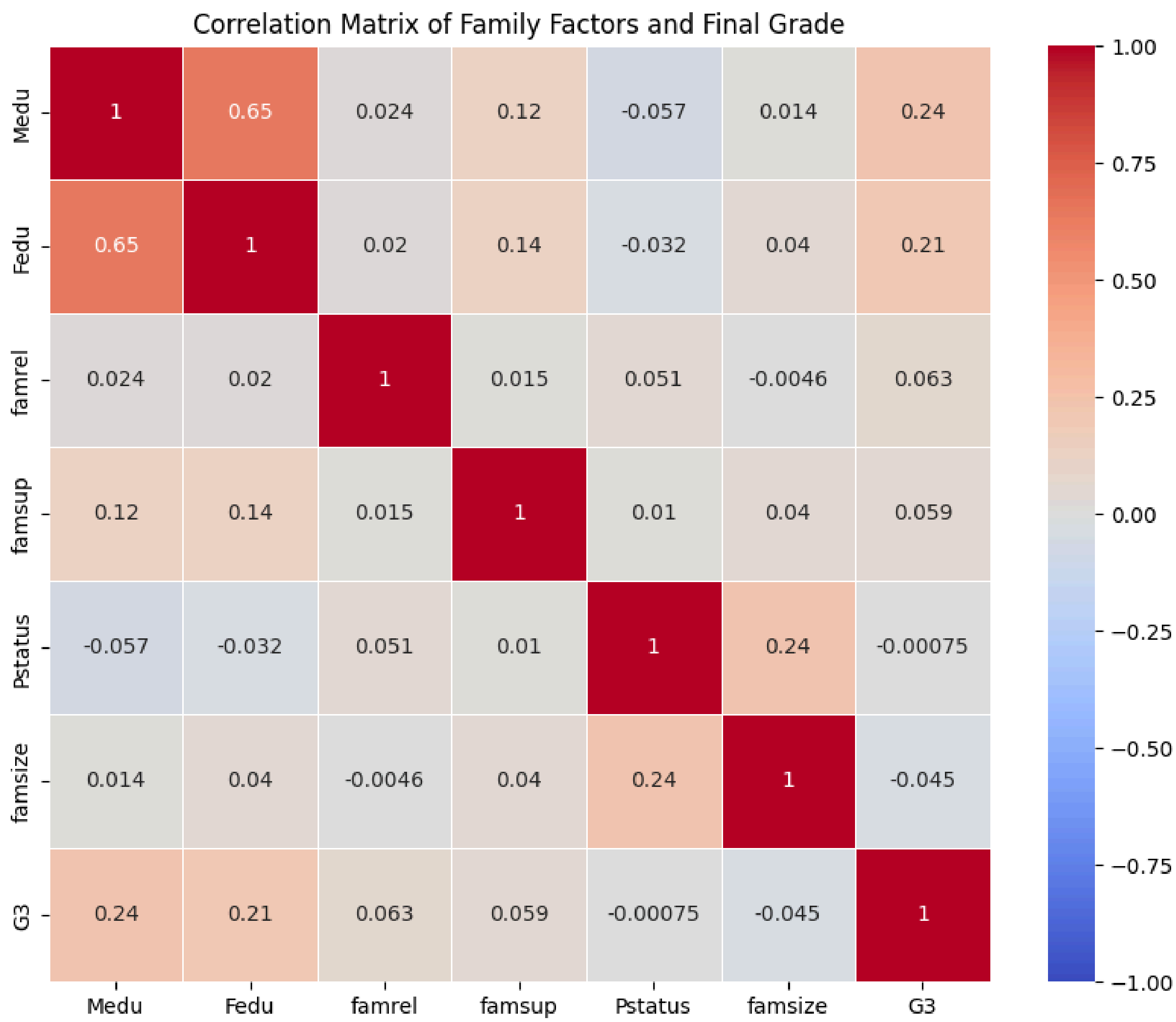
In [21]:
```python
plt.figure(figsize=(10, 6))
sns.boxplot(x='famsize', y='G3', data=porData)
plt.title('Family Size vs Final Grades')
plt.xlabel('Family Size (LE3: ≤3, GT3: >3)')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)
plt.show()
```



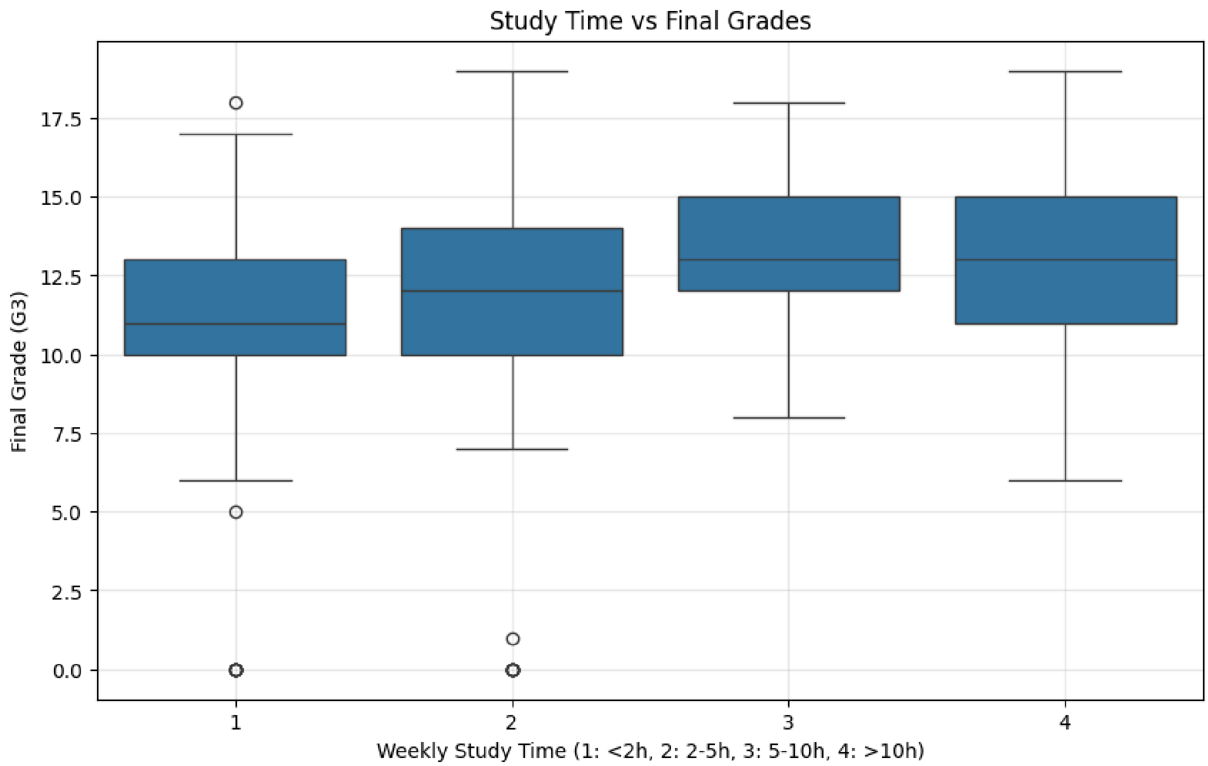
In [22]:

```
familyData = porData[familyFactors + ['G3']].copy()

familyData['famsup'] = familyData['famsup'].map({'yes': 1, 'no': 0})
familyData['Pstatus'] = familyData['Pstatus'].map({'T': 1, 'A': 0})
familyData['famsize'] = familyData['famsize'].map({'GT3': 1, 'LE3': 0})

familyGradeCorr = familyData.corr()
print("\nCorrelation between family factors and final grade:")
display(familyGradeCorr['G3'].sort_values(ascending=False))

plt.figure(figsize=(10, 8))
sns.heatmap(familyGradeCorr, annot=True, cmap='coolwarm', vmin=-1, vmax=1, l
plt.title('Correlation Matrix of Family Factors and Final Grade')
plt.show()
```

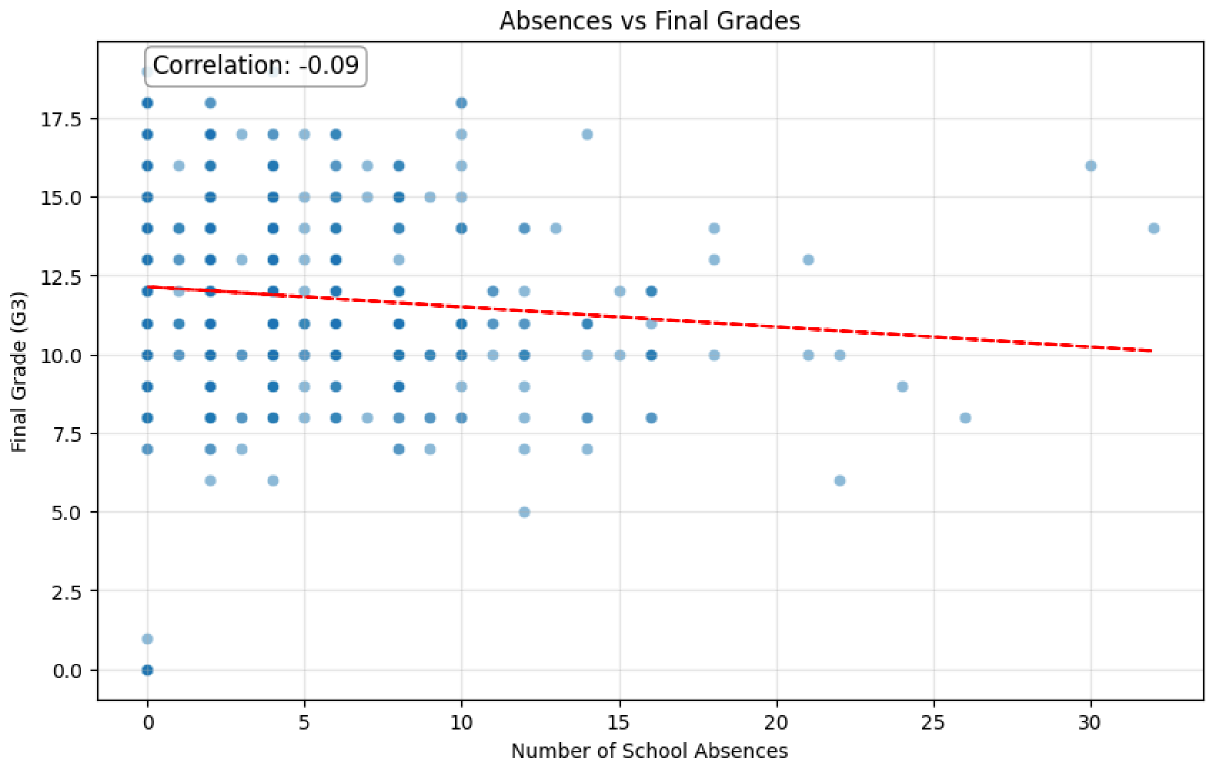
```
Correlation between family factors and final grade:
G3         1.000000
Medu       0.240151
Fedu       0.211800
famrel     0.063361
famsup     0.059206
Pstatus   -0.000754
famsize   -0.045016
Name: G3, dtype: float64
```



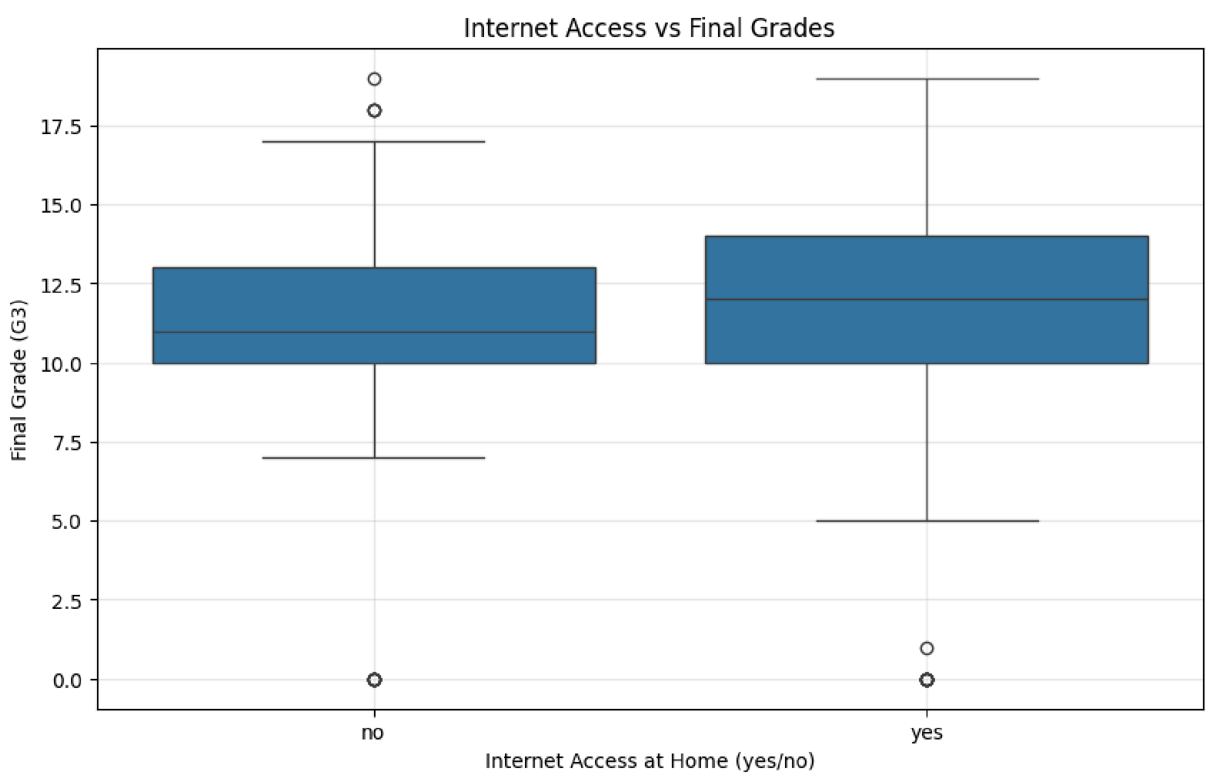
In [23]:
```
studyVars = ['studytime', 'absences', 'internet', 'schoolsup', 'paid']

plt.figure(figsize=(10, 6))
sns.boxplot(x='studytime', y='G3', data=porData)
plt.title('Study Time vs Final Grades')
plt.xlabel('Weekly Study Time (1: <2h, 2: 2-5h, 3: 5-10h, 4: >10h)')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)
plt.show()
```



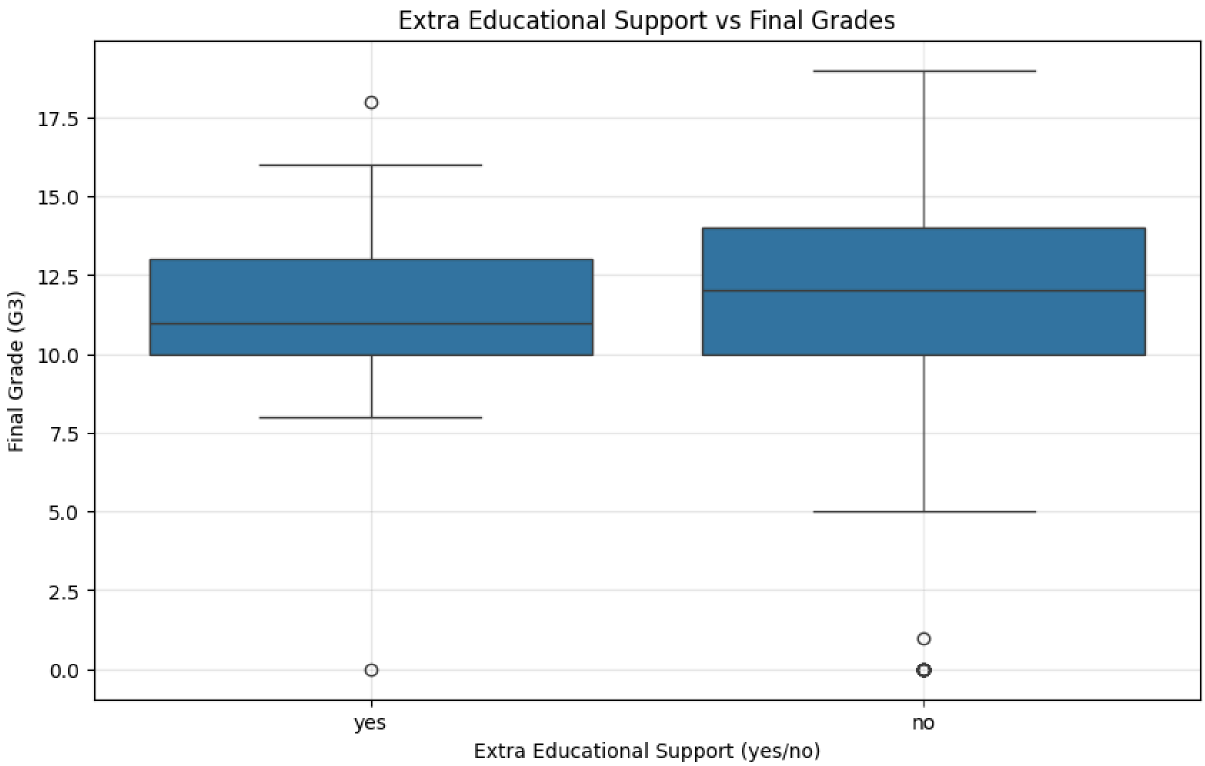
In [24]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='absences', y='G3', data=porData, alpha=0.5)
plt.title('Absences vs Final Grades')
plt.xlabel('Number of School Absences')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)

x = porData['absences']
y = porData['G3']
z = np.polyfit(x, y, 1)
p = np.poly1d(z)
plt.plot(x, p(x), "r--")

corr = porData['absences'].corr(porData['G3'])
plt.annotate(f"Correlation: {corr:.2f}", xy=(0.05, 0.95), xycoords='axes fra
             fontsize=12, bbox=dict(boxstyle="round,pad=0.3", fc="white", ec
plt.show()
```



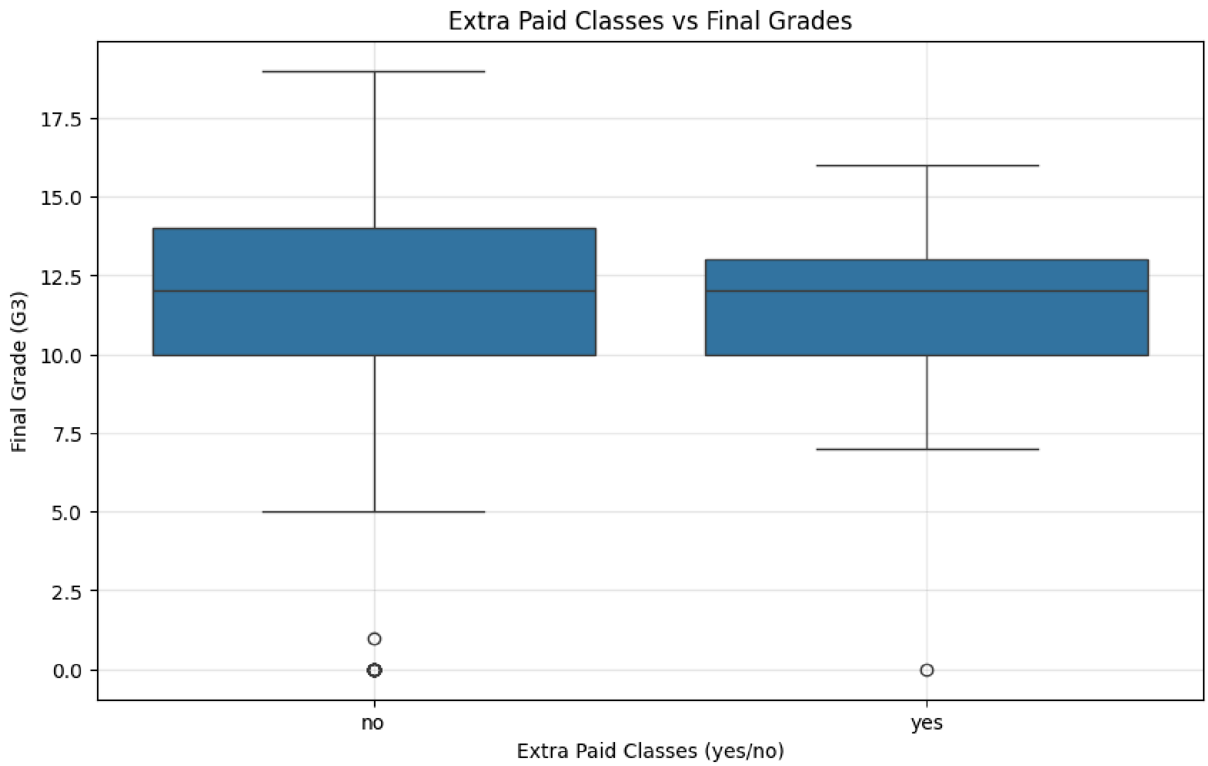
In [25]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x='internet', y='G3', data=porData)
plt.title('Internet Access vs Final Grades')
plt.xlabel('Internet Access at Home (yes/no)')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)
plt.show()
```



In [26]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x='schoolsup', y='G3', data=porData)
plt.title('Extra Educational Support vs Final Grades')
plt.xlabel('Extra Educational Support (yes/no)')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)
plt.show()
```



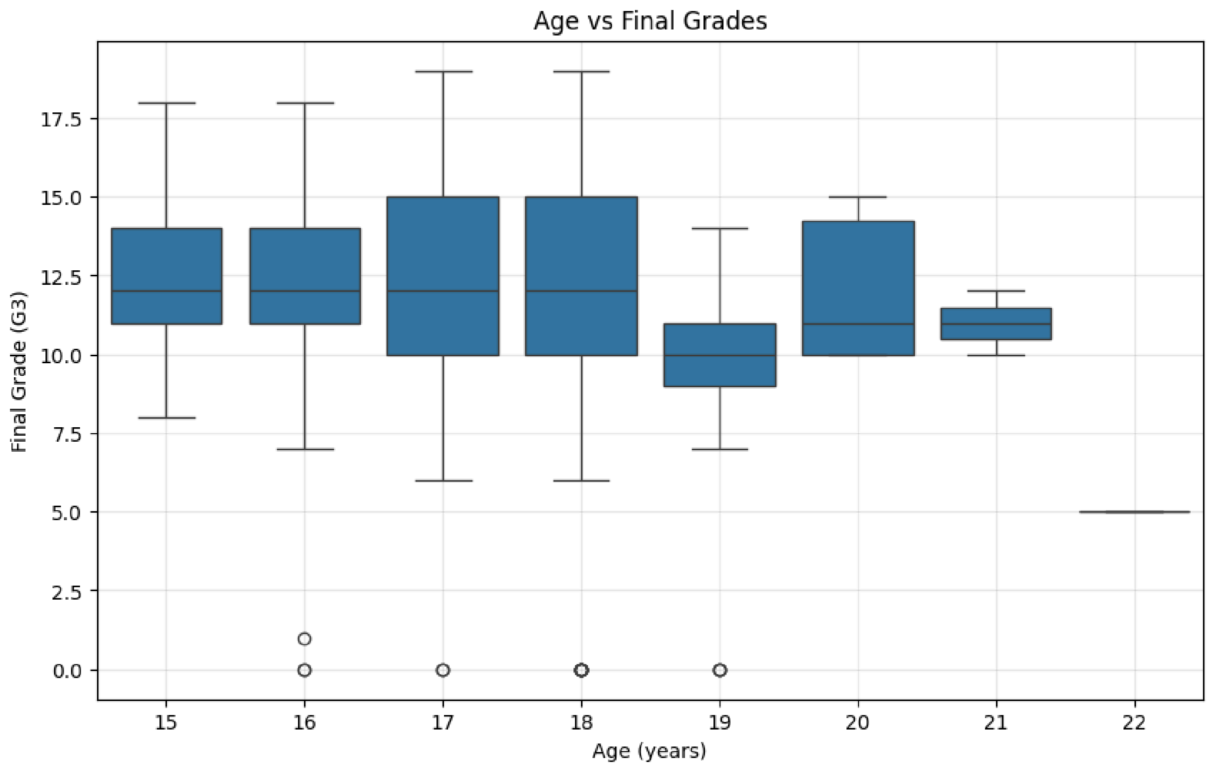
In [27]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x='paid', y='G3', data=porData)
plt.title('Extra Paid Classes vs Final Grades')
plt.xlabel('Extra Paid Classes (yes/no)')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)
plt.show()
```



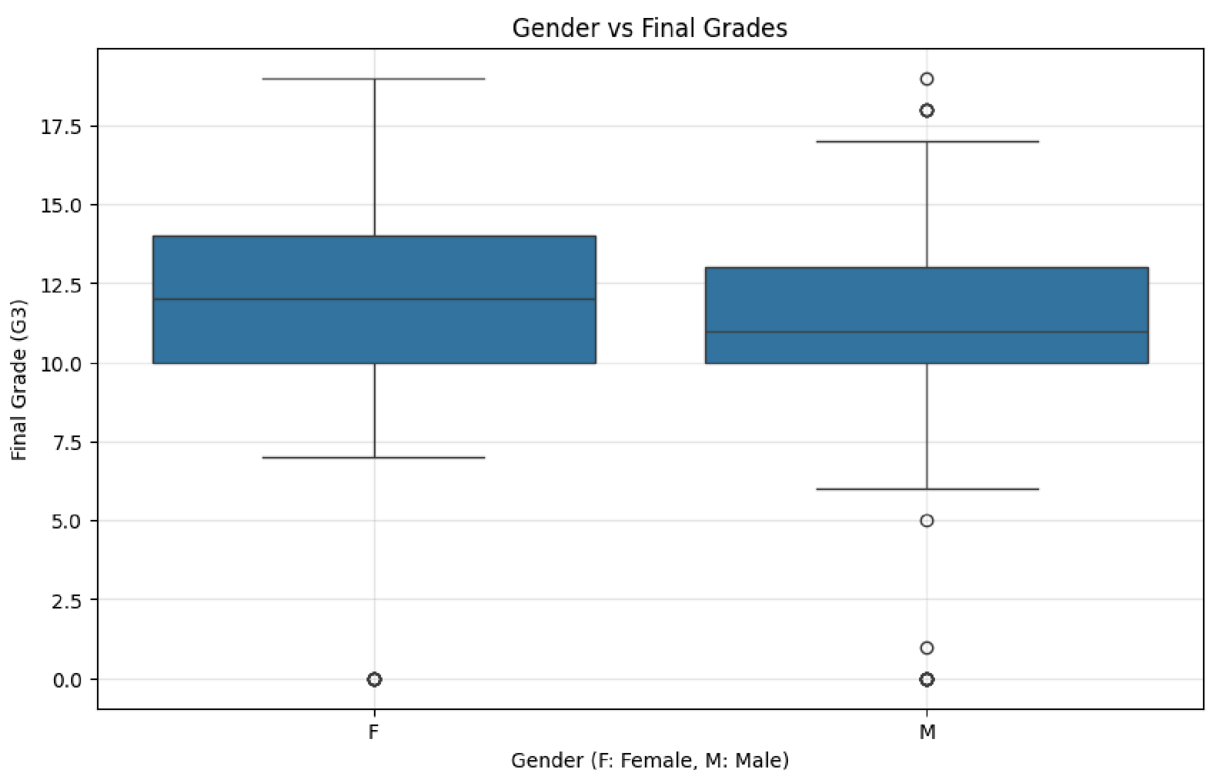
In [28]:
```
studyData = porData[studyVars + ['G3']].copy()
studyData['internet'] = studyData['internet'].map({'yes': 1, 'no': 0})
studyData['schoolsup'] = studyData['schoolsup'].map({'yes': 1, 'no': 0})
studyData['paid'] = studyData['paid'].map({'yes': 1, 'no': 0})

studyGradeCorr = studyData.corr()
print("\nCorrelation between study habits and final grade:")
display(studyGradeCorr['G3'].sort_values(ascending=False))

plt.figure(figsize=(10, 8))
sns.heatmap(studyGradeCorr, annot=True, cmap='coolwarm', vmin=-1, vmax=1, li
plt.title('Correlation Matrix of Study Habits and Final Grade')
plt.show()
```

```
Correlation between study habits and final grade:
G3            1.000000
studytime     0.249789
internet      0.150025
paid         -0.054898
schoolsup    -0.066405
absences     -0.091379
Name: G3, dtype: float64
```

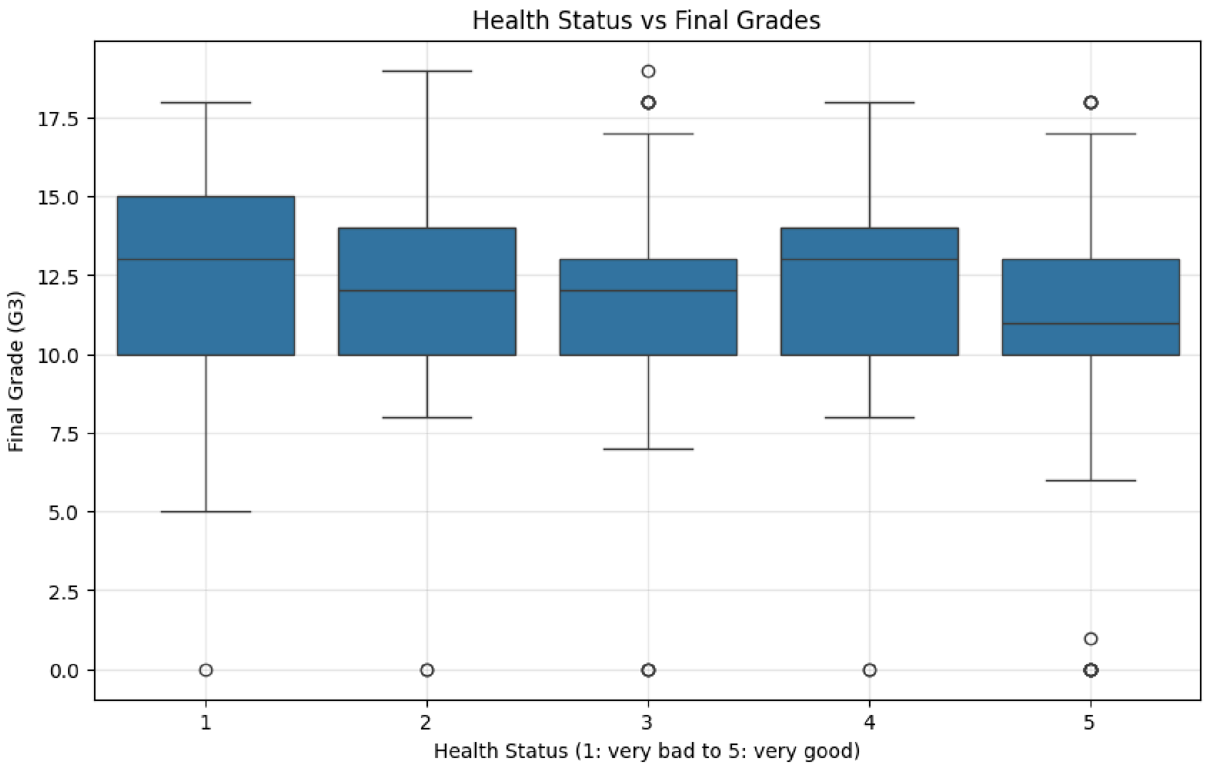
In [29]:
```
personalVars = ['age', 'sex', 'health', 'goout', 'romantic', 'Dalc', 'Walc',

plt.figure(figsize=(10, 6))
sns.boxplot(x='age', y='G3', data=porData)
plt.title('Age vs Final Grades')
plt.xlabel('Age (years)')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)
plt.show()
```



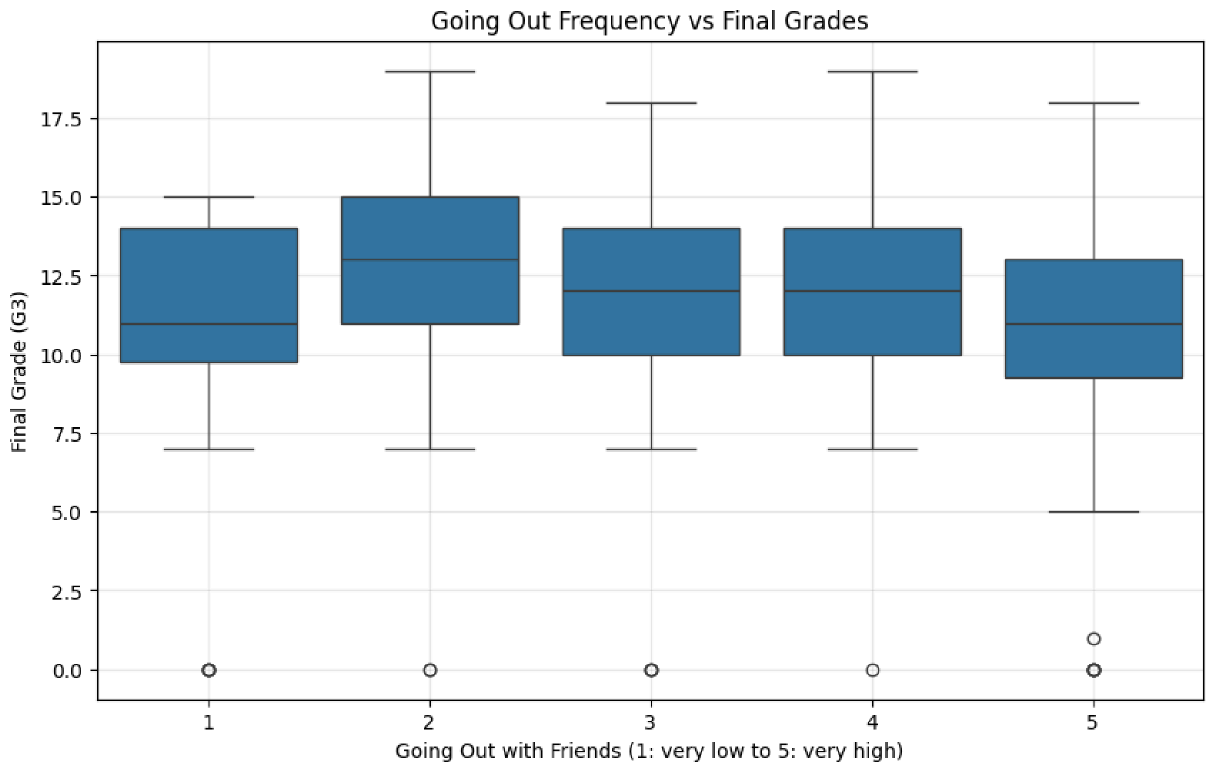
In [30]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x='sex', y='G3', data=porData)
plt.title('Gender vs Final Grades')
plt.xlabel('Gender (F: Female, M: Male)')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)
plt.show()
```



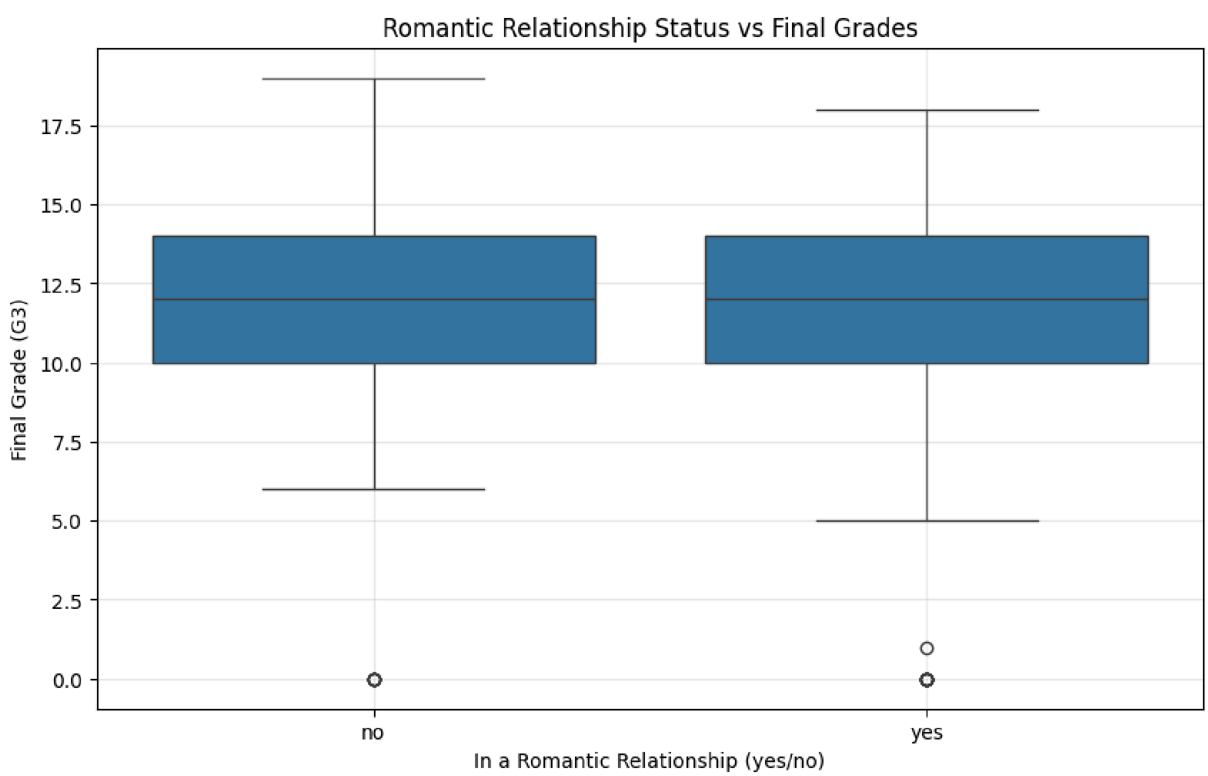
In [31]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x='health', y='G3', data=porData)
plt.title('Health Status vs Final Grades')
plt.xlabel('Health Status (1: very bad to 5: very good)')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)
plt.show()
```



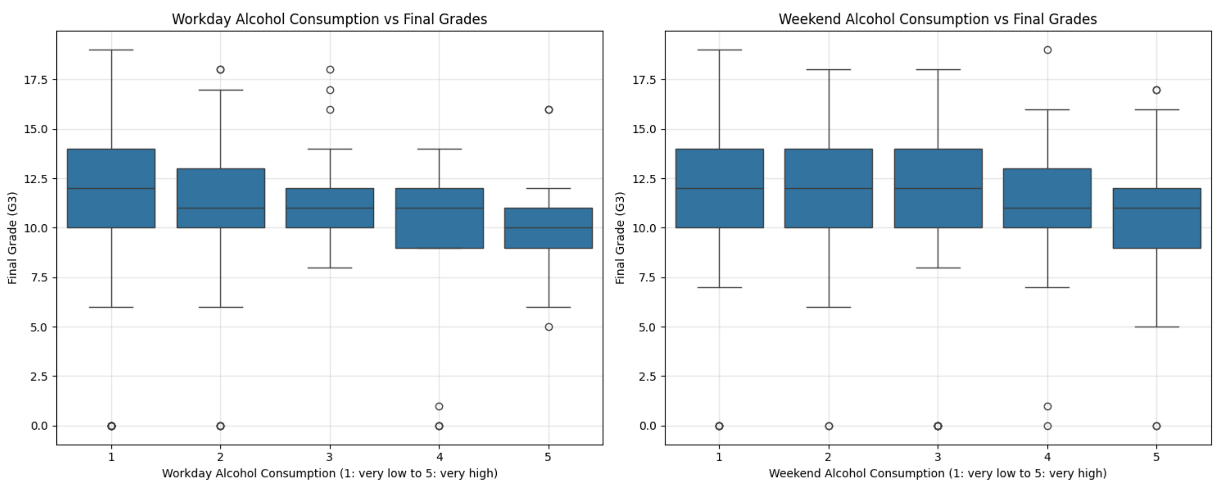
In [32]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x='goout', y='G3', data=porData)
plt.title('Going Out Frequency vs Final Grades')
plt.xlabel('Going Out with Friends (1: very low to 5: very high)')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)
plt.show()
```



In [33]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x='romantic', y='G3', data=porData)
plt.title('Romantic Relationship Status vs Final Grades')
plt.xlabel('In a Romantic Relationship (yes/no)')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)
plt.show()
```



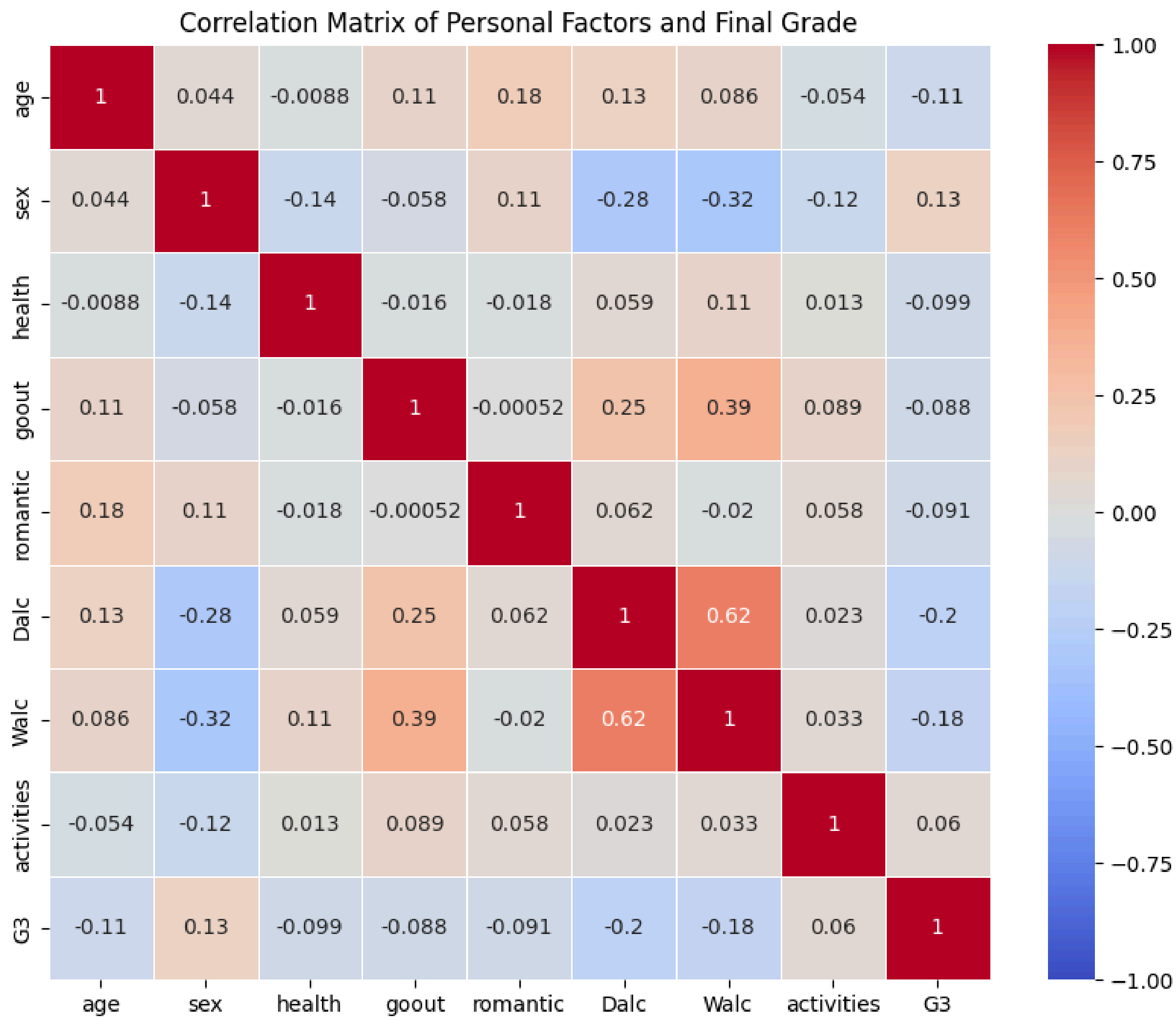
In [34]:
```
plt.figure(figsize=(15, 6))

plt.subplot(1, 2, 1)
sns.boxplot(x='Dalc', y='G3', data=porData)
plt.title('Workday Alcohol Consumption vs Final Grades')
plt.xlabel('Workday Alcohol Consumption (1: very low to 5: very high)')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)

plt.subplot(1, 2, 2)
sns.boxplot(x='Walc', y='G3', data=porData)
plt.title('Weekend Alcohol Consumption vs Final Grades')
plt.xlabel('Weekend Alcohol Consumption (1: very low to 5: very high)')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)

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



In [35]:
```
personalData = porData[personalVars + ['G3']].copy()
personalData['sex'] = personalData['sex'].map({'F': 1, 'M': 0})
personalData['romantic'] = personalData['romantic'].map({'yes': 1, 'no': 0})
if 'activities' in personalData.columns:
    personalData['activities'] = personalData['activities'].map({'yes': 1, '

personalGradeCorr = personalData.corr()
print("\nCorrelation between personal factors and final grade:")
display(personalGradeCorr['G3'].sort_values(ascending=False))

plt.figure(figsize=(10, 8))
sns.heatmap(personalGradeCorr, annot=True, cmap='coolwarm', vmin=-1, vmax=1,
plt.title('Correlation Matrix of Personal Factors and Final Grade')
plt.show()
```

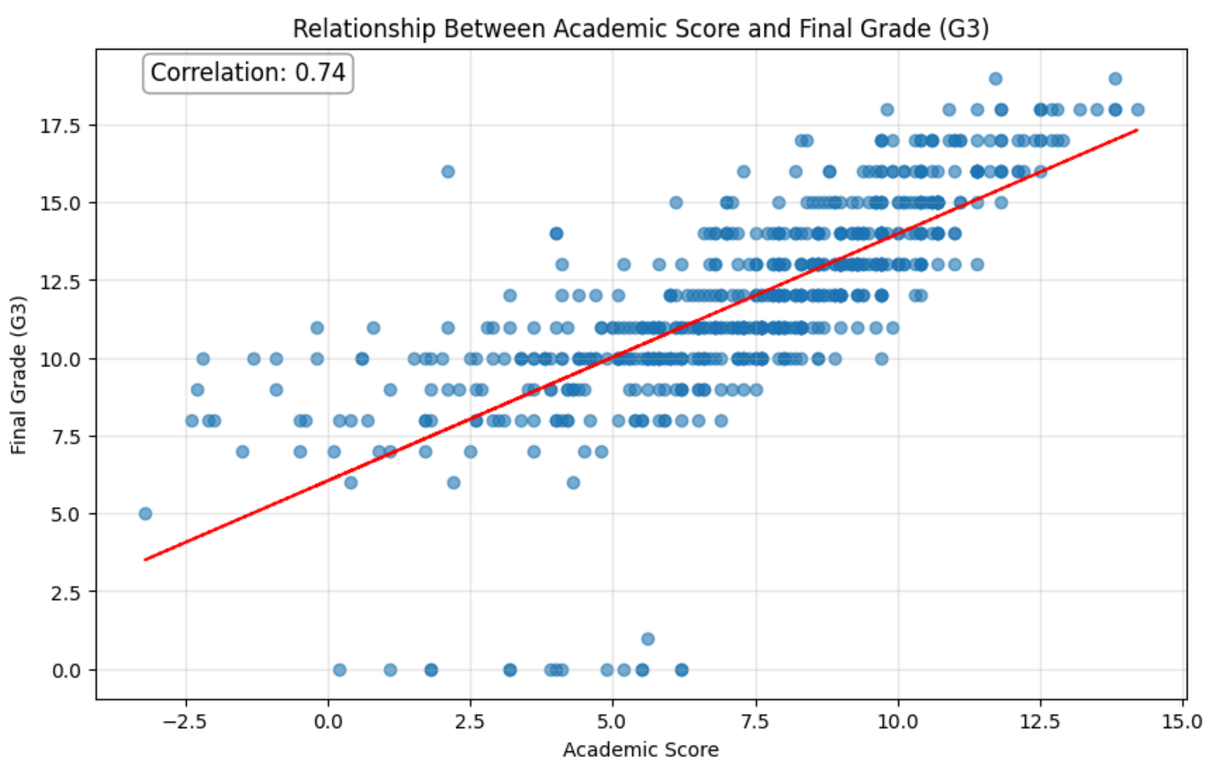
```
Correlation between personal factors and final grade:
```

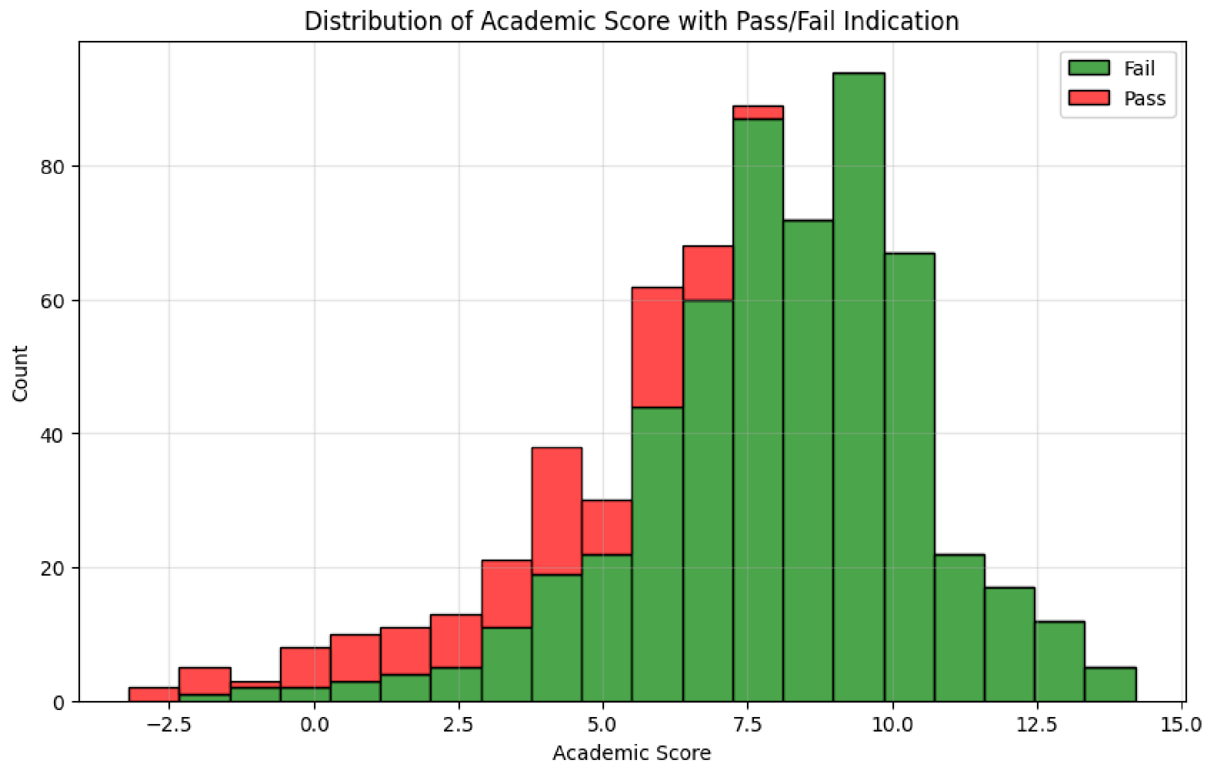
```
G3             1.000000
sex            0.129077
activities     0.059791
goout         -0.087641
romantic      -0.090583
health        -0.098851
age           -0.106505
Walc          -0.176619
Dalc          -0.204719
Name: G3, dtype: float64
```



In [36]:
```python
porData['Academic_Score'] = (0.7 * porData['G1']) - (2 * porData['failures']

plt.figure(figsize=(10, 6))
plt.scatter(porData['Academic_Score'], porData['G3'], alpha=0.6)
plt.title('Relationship Between Academic Score and Final Grade (G3)')
plt.xlabel('Academic Score')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)

x = porData['Academic_Score']
y = porData['G3']
z = np.polyfit(x, y, 1)
p = np.poly1d(z)
plt.plot(x, p(x), "r--")
```

```
corr = porData['Academic_Score'].corr(porData['G3'])
plt.annotate(f"Correlation: {corr:.2f}", xy=(0.05, 0.95), xycoords='axes fra
             fontsize=12, bbox=dict(boxstyle="round,pad=0.3", fc="white", ec

plt.show()

plt.figure(figsize=(10, 6))
sns.histplot(data=porData, x='Academic_Score', hue=porData['G3'] >= passThre
             multiple="stack", palette=['red', 'green'], alpha=0.7, bins=20)
plt.title('Distribution of Academic Score with Pass/Fail Indication')
plt.xlabel('Academic Score')
plt.ylabel('Count')
plt.legend(['Fail', 'Pass'])
plt.grid(True, alpha=0.3)
plt.show()

print(f"Correlation between Academic Score and G3: {corr:.4f}")

thresholds = np.linspace(porData['Academic_Score'].min(), porData['Academic_
accuracies = []

for threshold in thresholds:
    predicted_pass = porData['Academic_Score'] >= threshold
    actual_pass = porData['G3'] >= passThreshold
    accuracy = np.mean(predicted_pass == actual_pass)
    accuracies.append(accuracy)

best_threshold = thresholds[np.argmax(accuracies)]
best_accuracy = np.max(accuracies)

print(f"Best Academic Score threshold for predicting pass/fail: {best_thresh
print(f"Accuracy at this threshold: {best_accuracy:.2f}")
```

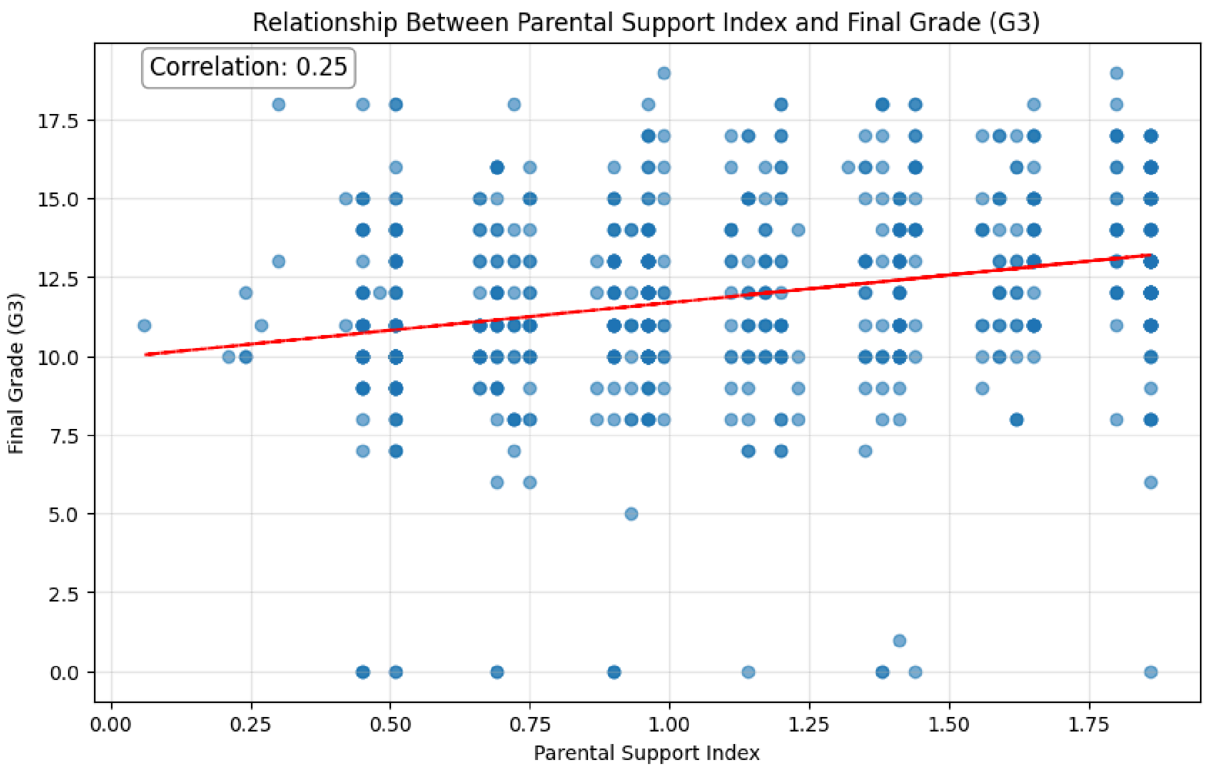


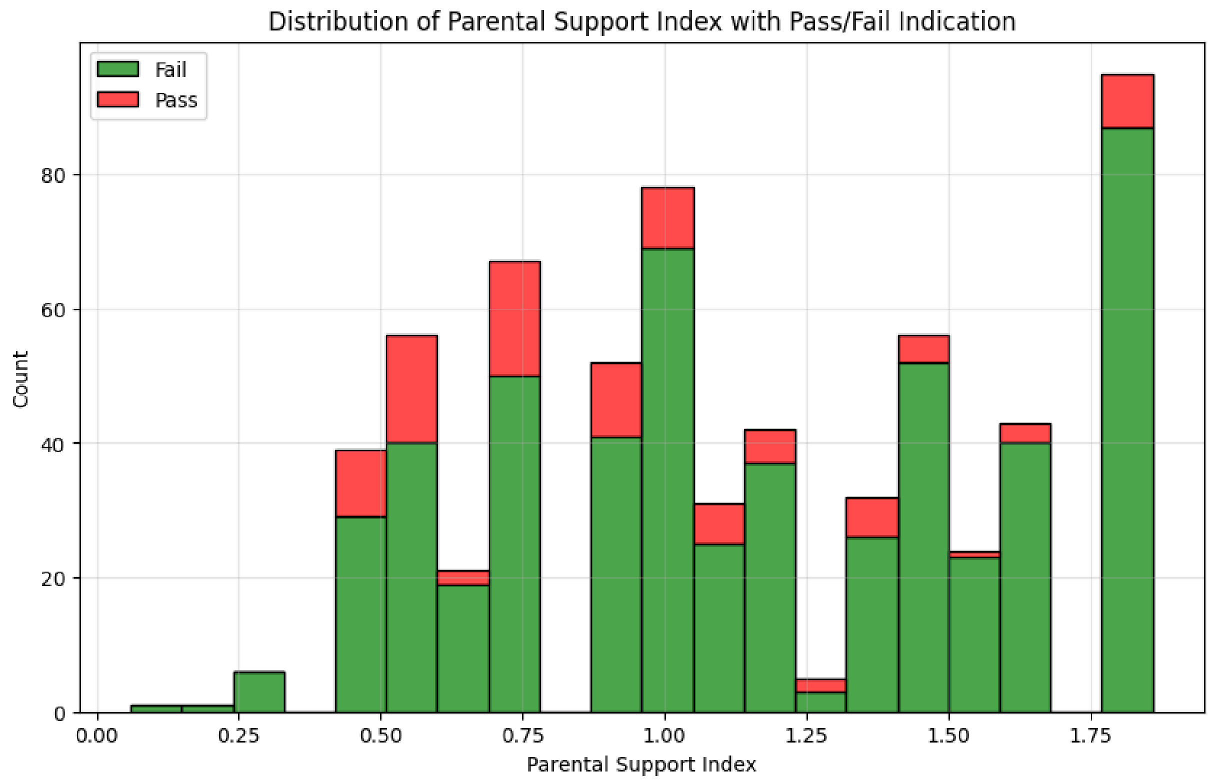



```
Correlation between Academic Score and G3: 0.7354
Best Academic Score threshold for predicting pass/fail: 4.36
Accuracy at this threshold: 0.88
```

In [37]:
```
porData['Parental_Support'] = (0.24 * porData['Medu']) + (0.21 * porData['Fe

plt.figure(figsize=(10, 6))
plt.scatter(porData['Parental_Support'], porData['G3'], alpha=0.6)
plt.title('Relationship Between Parental Support Index and Final Grade (G3)'
plt.xlabel('Parental Support Index')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)

x = porData['Parental_Support']
y = porData['G3']
z = np.polyfit(x, y, 1)
p = np.poly1d(z)
plt.plot(x, p(x), "r--")

corr = porData['Parental_Support'].corr(porData['G3'])
plt.annotate(f"Correlation: {corr:.2f}", xy=(0.05, 0.95), xycoords='axes fra
             fontsize=12, bbox=dict(boxstyle="round,pad=0.3", fc="white", ec

plt.show()

plt.figure(figsize=(10, 6))
sns.histplot(data=porData, x='Parental_Support', hue=porData['G3'] >= passTh
             multiple="stack", palette=['red', 'green'], alpha=0.7, bins=20)
plt.title('Distribution of Parental Support Index with Pass/Fail Indication'
plt.xlabel('Parental Support Index')
plt.ylabel('Count')
plt.legend(['Fail', 'Pass'])
plt.grid(True, alpha=0.3)
```

```
plt.show()

print(f"Correlation between Parental Support Index and G3: {corr:.4f}")

thresholds = np.linspace(porData['Parental_Support'].min(), porData['Parenta
accuracies = []

for threshold in thresholds:
    predicted_pass = porData['Parental_Support'] >= threshold
    actual_pass = porData['G3'] >= passThreshold
    accuracy = np.mean(predicted_pass == actual_pass)
    accuracies.append(accuracy)

best_threshold = thresholds[np.argmax(accuracies)]
best_accuracy = np.max(accuracies)

print(f"Best Parental Support Index threshold for predicting pass/fail: {bes
print(f"Accuracy at this threshold: {best_accuracy:.2f}")
```

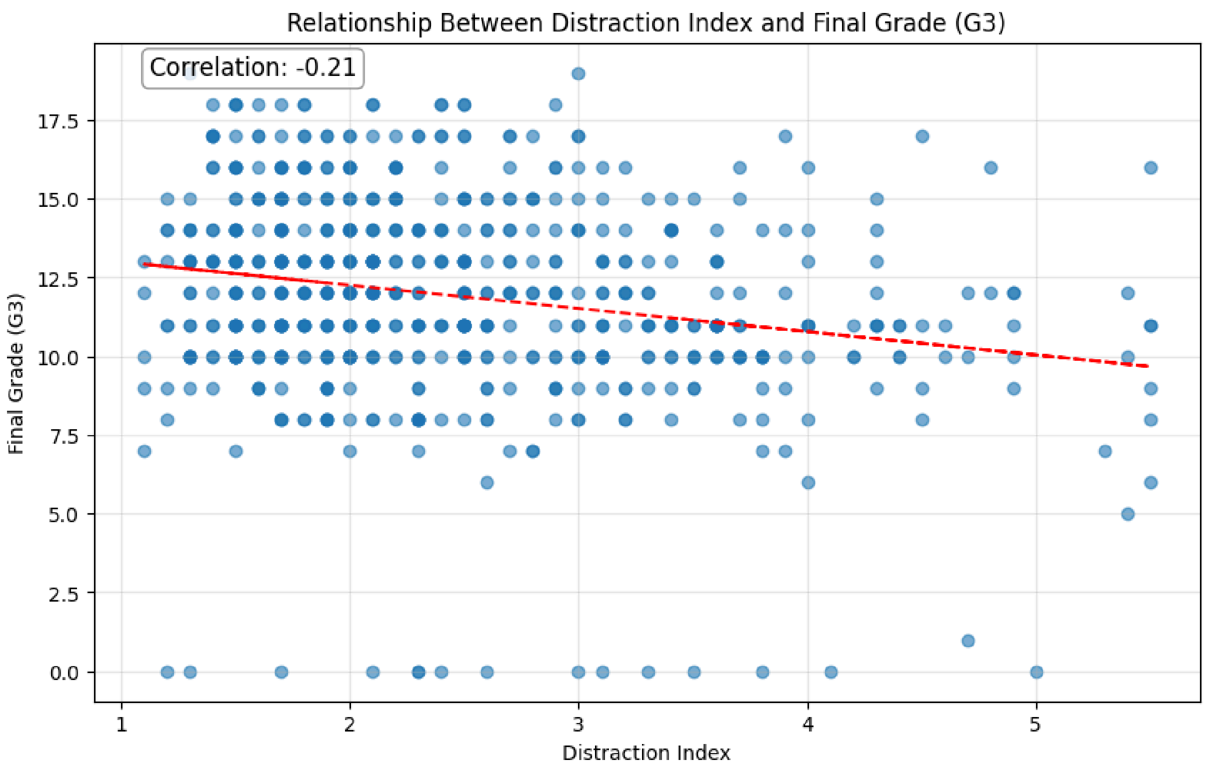


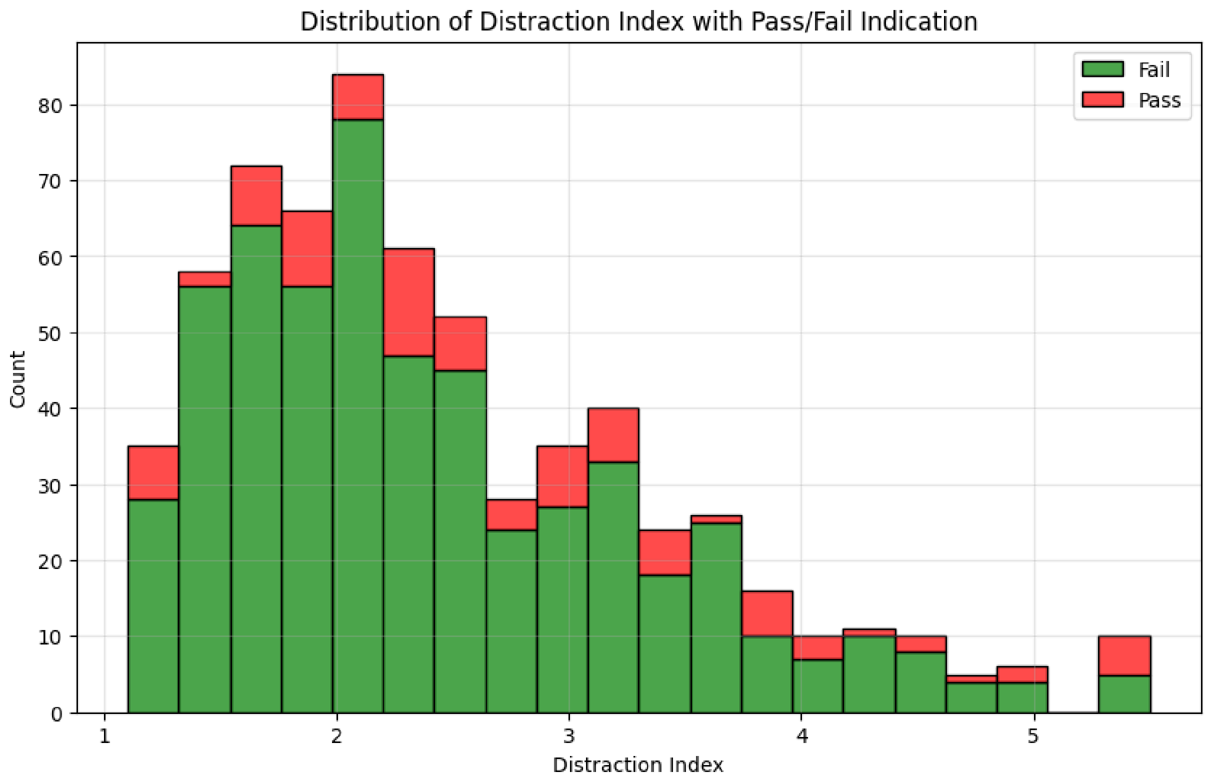



```
Correlation between Parental Support Index and G3: 0.2511
Best Parental Support Index threshold for predicting pass/fail: 0.06
Accuracy at this threshold: 0.85
```

In [38]:
```
porData['Distraction_Index'] = (0.2 * porData['goout']) + (0.4 * porData['Wa

plt.figure(figsize=(10, 6))
plt.scatter(porData['Distraction_Index'], porData['G3'], alpha=0.6)
plt.title('Relationship Between Distraction Index and Final Grade (G3)')
plt.xlabel('Distraction Index')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)

x = porData['Distraction_Index']
y = porData['G3']
z = np.polyfit(x, y, 1)
p = np.poly1d(z)
plt.plot(x, p(x), "r--")

corr = porData['Distraction_Index'].corr(porData['G3'])
plt.annotate(f"Correlation: {corr:.2f}", xy=(0.05, 0.95), xycoords='axes fra
             fontsize=12, bbox=dict(boxstyle="round,pad=0.3", fc="white", ec

plt.show()

plt.figure(figsize=(10, 6))
sns.histplot(data=porData, x='Distraction_Index', hue=porData['G3'] >= passT
             multiple="stack", palette=['red', 'green'], alpha=0.7, bins=20)
plt.title('Distribution of Distraction Index with Pass/Fail Indication')
plt.xlabel('Distraction Index')
plt.ylabel('Count')
plt.legend(['Fail', 'Pass'])
plt.grid(True, alpha=0.3)
```

```
plt.show()

print(f"Correlation between Distraction Index and G3: {corr:.4f}")


thresholds = np.linspace(porData['Distraction_Index'].min(), porData['Distra
accuracies = []

for threshold in thresholds:
    # For Distraction Index, LOWER values predict passing
    predicted_pass = porData['Distraction_Index'] <= threshold
    actual_pass = porData['G3'] >= passThreshold
    accuracy = np.mean(predicted_pass == actual_pass)
    accuracies.append(accuracy)

best_threshold = thresholds[np.argmax(accuracies)]
best_accuracy = np.max(accuracies)

print(f"Best Distraction Index threshold for predicting pass/fail: {best_thr
print(f"Accuracy at this threshold: {best_accuracy:.2f}")
```

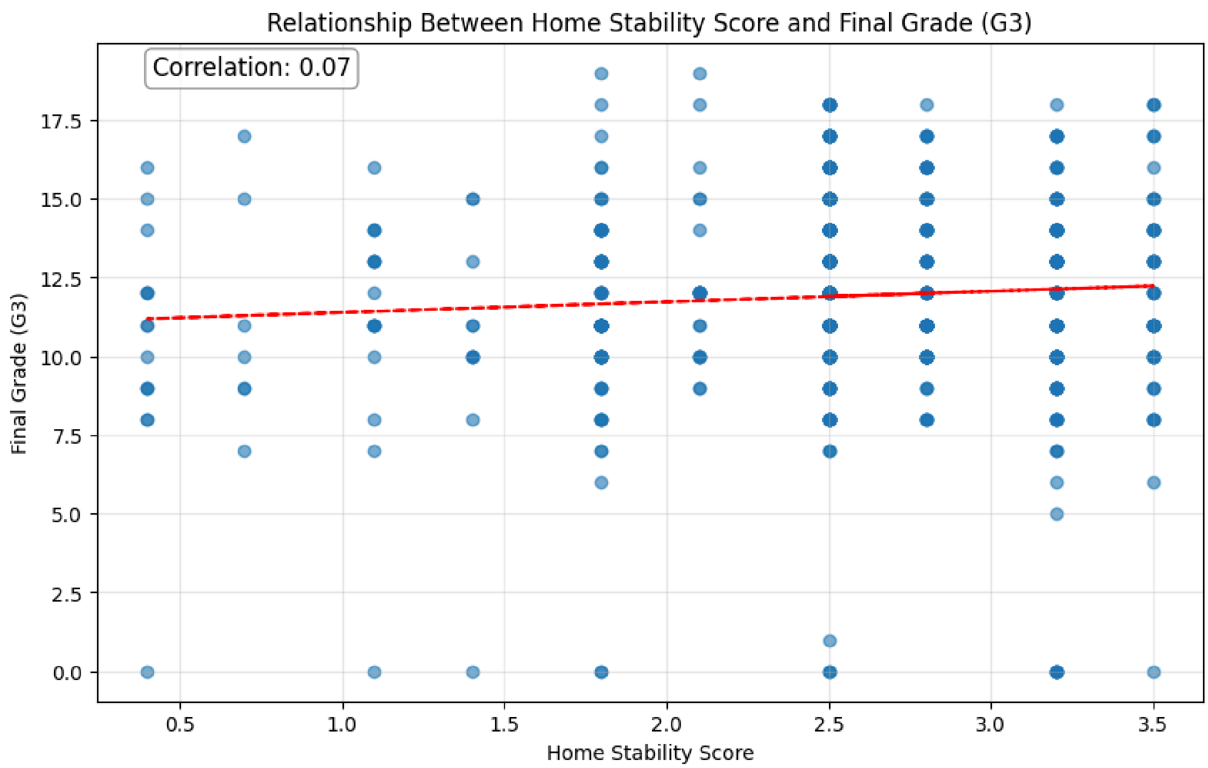


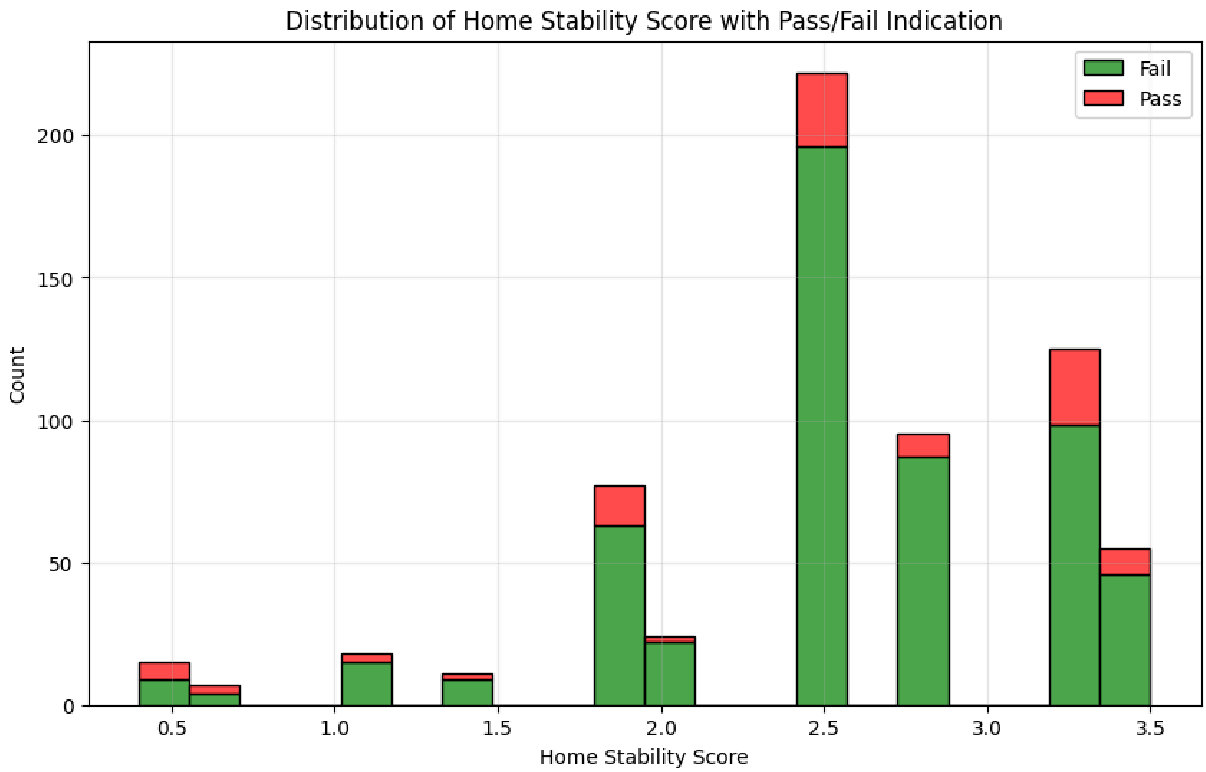



```
Correlation between Distraction Index and G3: -0.2136
Best Distraction Index threshold for predicting pass/fail: 4.92
Accuracy at this threshold: 0.85
```

In [39]:
```python
porData['famsize_num'] = porData['famsize'].map({'GT3': 1, 'LE3': 0})
porData['Pstatus_num'] = porData['Pstatus'].map({'T': 1, 'A': 0})

porData['Home_Stability'] = (0.7 * porData['famrel']) - (0.3 * porData['fams

plt.figure(figsize=(10, 6))
plt.scatter(porData['Home_Stability'], porData['G3'], alpha=0.6)
plt.title('Relationship Between Home Stability Score and Final Grade (G3)')
plt.xlabel('Home Stability Score')
plt.ylabel('Final Grade (G3)')
plt.grid(True, alpha=0.3)

x = porData['Home_Stability']
y = porData['G3']
z = np.polyfit(x, y, 1)
p = np.poly1d(z)
plt.plot(x, p(x), "r--")

corr = porData['Home_Stability'].corr(porData['G3'])
plt.annotate(f"Correlation: {corr:.2f}", xy=(0.05, 0.95), xycoords='axes fra
             fontsize=12, bbox=dict(boxstyle="round,pad=0.3", fc="white", ec

plt.show()

plt.figure(figsize=(10, 6))
sns.histplot(data=porData, x='Home_Stability', hue=porData['G3'] >= passThre
             multiple="stack", palette=['red', 'green'], alpha=0.7, bins=20)
plt.title('Distribution of Home Stability Score with Pass/Fail Indication')
plt.xlabel('Home Stability Score')
```

```
plt.ylabel('Count')
plt.legend(['Fail', 'Pass'])
plt.grid(True, alpha=0.3)
plt.show()
print(f"Correlation between Home Stability Score and G3: {corr:.4f}")

thresholds = np.linspace(porData['Home_Stability'].min(), porData['Home_Stab
accuracies = []

for threshold in thresholds:
    predicted_pass = porData['Home_Stability'] >= threshold
    actual_pass = porData['G3'] >= passThreshold
    accuracy = np.mean(predicted_pass == actual_pass)
    accuracies.append(accuracy)

best_threshold = thresholds[np.argmax(accuracies)]
best_accuracy = np.max(accuracies)

print(f"Best Home Stability Score threshold for predicting pass/fail: {best_
print(f"Accuracy at this threshold: {best_accuracy:.2f}")
```






```
Correlation between Home Stability Score and G3: 0.0710
Best Home Stability Score threshold for predicting pass/fail: 0.40
Accuracy at this threshold: 0.85
```

In [40]:
```
def prepareData(X, y, testSize=0.3, randomState=42, stratify=None):
    if stratify is not None:
        X_train, X_test, y_train, y_test = train_test_split(
            X, y, test_size=testSize, random_state=randomState, stratify=str
    else:
        X_train, X_test, y_train, y_test = train_test_split(
            X, y, test_size=testSize, random_state=randomState)

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

    return X_train_scaled, X_test_scaled, y_train, y_test, scaler
```

In [45]:
```
def categorizeGrades(grade):
   if grade >= 16:
       return 1
   elif grade >= 14:
       return 2
   elif grade >= 12:
       return 3
   elif grade >= 10:
       return 4
   else:
       return 5

porData['gradeCategory'] = porData['G3'].apply(categorizeGrades)
porData['passFail'] = (porData['G3'] >= 10).astype(int)
```

```python
if porData['internet'].dtype == 'object':
    porData['internet'] = porData['internet'].map({'yes': 1, 'no': 0})

ordinalFeatures = [
    'G1',
    'failures',
    'studytime',
    'absences',
    'Parental_Support',
    'Distraction_Index',
    'internet'
]

xOrd = porData[ordinalFeatures]
yOrd = porData['gradeCategory']
xOrdTrainScaled, xOrdTestScaled, yOrdTrain, yOrdTest, scalerOrd = prepareDat

xOrdTrainDF = pd.DataFrame(xOrdTrainScaled, columns=ordinalFeatures)
xOrdTestDF = pd.DataFrame(xOrdTestScaled, columns=ordinalFeatures)
yOrdTrain = pd.Series(yOrdTrain).reset_index(drop=True)
yOrdTest = pd.Series(yOrdTest).reset_index(drop=True)

ordinalModel = OrderedModel(yOrdTrain, xOrdTrainDF, distr='logit')
ordinalResult = ordinalModel.fit(method='bfgs', maxiter=1000)
print(ordinalResult.summary())

probabilities = ordinalResult.predict(xOrdTestDF)
yOrdPred = probabilities.idxmax(axis=1)
accuracy = accuracy_score(yOrdTest, yOrdPred)
accuracyScoresOrd = [accuracy]
avgAccuracy = accuracy
print(f"Ordinal Logistic Regression Accuracy: {avgAccuracy:.4f}")

featureImportance = {}
featureImportance[1] = dict(zip(ordinalFeatures, ordinalResult.params[:len(c

for gradeLevel, importance in featureImportance.items():
    print(f"\nFeature importance for ordinal model:")
    sortedImportance = {k: v for k, v in sorted(importance.items(),
                        key=lambda item: abs(item[1]), reverse=True)}
    for feature, coef in sortedImportance.items():
        print(f"{feature}: {coef:.4f}")

def ordinal_cv_score(X, y, cv=5):
    fold_scores = []
    kf = KFold(n_splits=cv, shuffle=True, random_state=42)

    for train_idx, test_idx in kf.split(X):
        X_train_fold, X_test_fold = X.iloc[train_idx], X.iloc[test_idx]
        y_train_fold, y_test_fold = y.iloc[train_idx], y.iloc[test_idx]

        X_train_fold_scaled = scalerOrd.fit_transform(X_train_fold)
        X_test_fold_scaled = scalerOrd.transform(X_test_fold)

        X_train_fold_df = pd.DataFrame(X_train_fold_scaled, columns=ordinalFe
        X_test_fold_df = pd.DataFrame(X_test_fold_scaled, columns=ordinalFeat
```

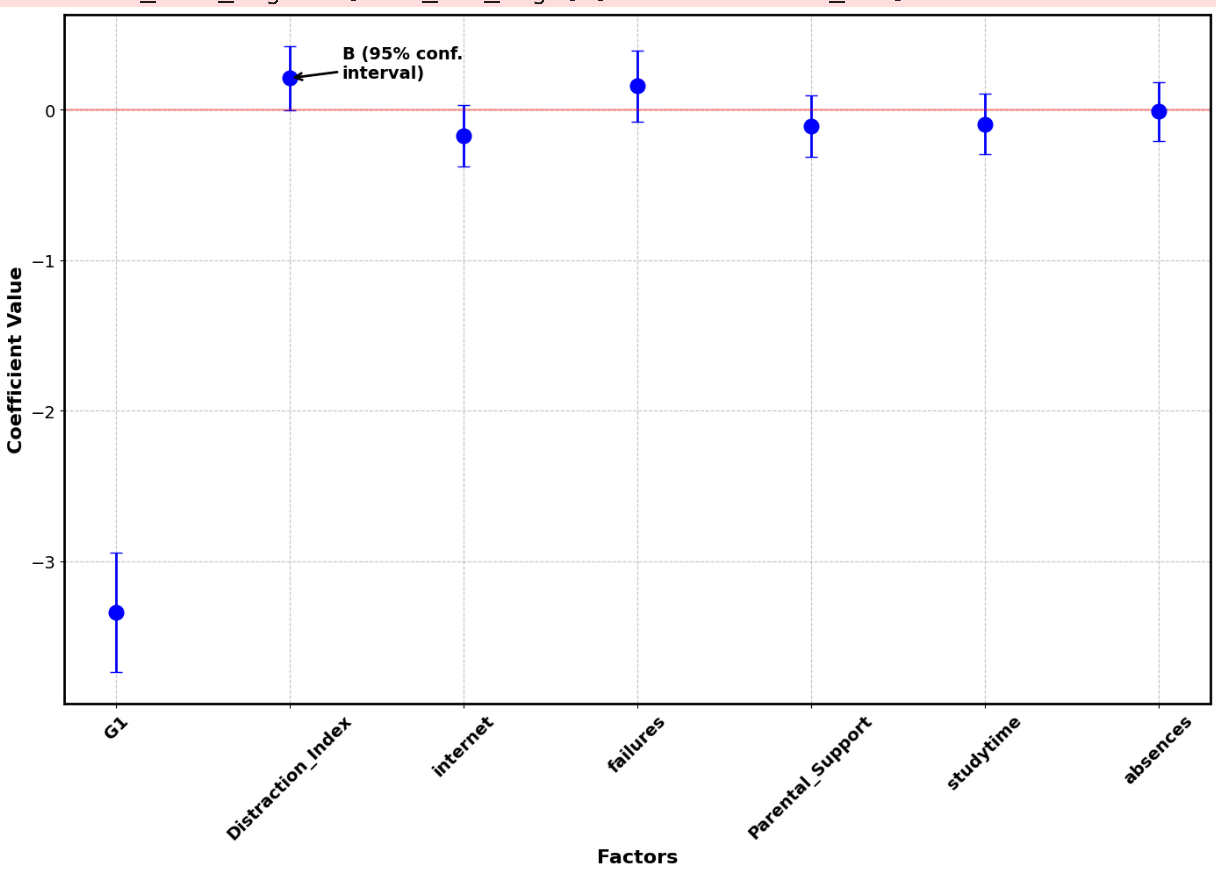
```python
        X_train_fold_df = X_train_fold_df.reset_index(drop=True)
        X_test_fold_df = X_test_fold_df.reset_index(drop=True)
        y_train_fold = pd.Series(y_train_fold.values).reset_index(drop=True)
        y_test_fold = pd.Series(y_test_fold.values).reset_index(drop=True)

        try:
            model = OrderedModel(y_train_fold, X_train_fold_df, distr='logit'
            result = model.fit(method='bfgs', maxiter=1000, disp=0)
            probs = result.predict(X_test_fold_df)
            preds = probs.idxmax(axis=1)
            fold_scores.append(accuracy_score(y_test_fold, preds))
        except Exception as e:
            print(f"Warning: Issue in a fold: {e}")

    return np.mean(fold_scores) if fold_scores else None

cvScore = ordinal_cv_score(xOrd, yOrd, cv=5)
cvScores = [cvScore]
print(f"5-fold CV accuracy for ordinal logistic regression: {cvScore:.4f}")

# MODIFIED FIGURE CODE STARTS HERE
plt.figure(figsize=(14, 10))  # Increased figure size

# Get the coefficients and their 95% confidence intervals
coefs = ordinalResult.params[:len(ordinalFeatures)]
errs = ordinalResult.bse[:len(ordinalFeatures)]
conf_int_low = coefs - 1.96 * errs  # 95% confidence interval lower bound
conf_int_high = coefs + 1.96 * errs  # 95% confidence interval upper bound

# Sort features by coefficient absolute magnitude
sort_idx = np.argsort(np.abs(coefs))[::-1]
sorted_features = [ordinalFeatures[i] for i in sort_idx]
sorted_coefs = [coefs[i] for i in sort_idx]
sorted_conf_low = [conf_int_low[i] for i in sort_idx]
sorted_conf_high = [conf_int_high[i] for i in sort_idx]

# Plot the coefficients with error bars showing 95% confidence intervals
plt.errorbar(
    range(len(sorted_features)),
    sorted_coefs,
    yerr=[
        [c - l for c, l in zip(sorted_coefs, sorted_conf_low)],  # lower err
        [h - c for c, h in zip(sorted_coefs, sorted_conf_high)]  # upper err
    ],
    fmt='o',
    capsize=5,
    markersize=12,  # Increased marker size
    ecolor='blue',
    color='blue',
    linewidth=2  # Thicker error bars
)

# Add a horizontal line at y=0
plt.axhline(y=0, color='r', linestyle='-', alpha=0.3, linewidth=2)
```

```
# Add labels and title with larger font sizes
plt.xlabel('Factors', fontsize=16, fontweight='bold')
plt.ylabel('Coefficient Value', fontsize=16, fontweight='bold')

# Set x-tick positions and labels with larger font size
plt.xticks(range(len(sorted_features)), sorted_features, rotation=45, fontsi
plt.yticks(fontsize=14)  # Larger y-tick labels

# Add grid lines for better readability
plt.grid(True, linestyle='--', alpha=0.7)

# Adjust layout to avoid cutting off labels
plt.tight_layout()

# Add a note for the "B" as shown in the sketch with larger font
plt.annotate('B (95% conf.\ninterval)',
             xy=(1, sorted_coefs[1]),
             xytext=(1.3, sorted_coefs[1]),
             fontsize=14,
             fontweight='bold',
             arrowprops=dict(arrowstyle="->", linewidth=2))

# Add a border to the figure
plt.gca().spines['top'].set_linewidth(2)
plt.gca().spines['right'].set_linewidth(2)
plt.gca().spines['bottom'].set_linewidth(2)
plt.gca().spines['left'].set_linewidth(2)

plt.show()
# MODIFIED FIGURE CODE ENDS HERE

unique_actual = np.unique(yOrdTest)
unique_pred = np.unique(yOrdPred)
category_names = ['Excellent', 'Very Good', 'Good', 'Sufficient', 'Fail']
label_indices = [1, 2, 3, 4, 5]

cm = confusion_matrix(yOrdTest, yOrdPred, labels=label_indices)

plt.figure(figsize=(10, 8))
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=category_r
disp.plot(cmap='Blues')
plt.show()

class_accuracy = cm.diagonal() / cm.sum(axis=1)

for i, category in enumerate(category_names):
   print(f"Accuracy for {category}: {class_accuracy[i]:.4f}")

precision, recall, _, _ = precision_recall_fscore_support(yOrdTest, yOrdPrec

for i, category in enumerate(category_names):
   print(f"{category}: Precision = {precision[i]:.4f}, Recall = {recall[i]:.
```

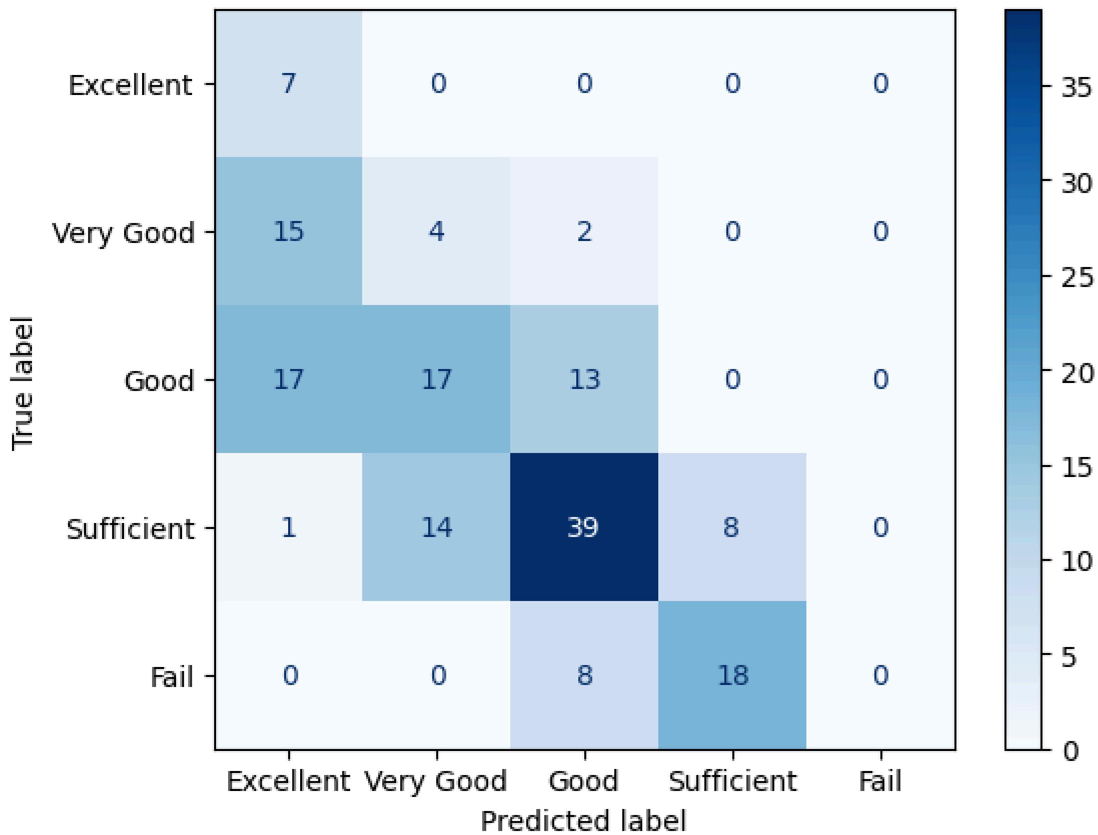
```
Optimization terminated successfully.
         Current function value: 0.888890
         Iterations: 26
         Function evaluations: 27
         Gradient evaluations: 27
                             OrderedModel Results
============================================================================
==
Dep. Variable:          gradeCategory   Log-Likelihood:                -403.
56
Model:                   OrderedModel   AIC:                             82
9.1
Method:            Maximum Likelihood   BIC:                             87
4.4
Date:                Sat, 12 Apr 2025
Time:                        21:58:50
No. Observations:                 454
Df Residuals:                     443
Df Model:                           7
============================================================================
=========
                        coef    std err          z      P>|z|      [0.025
0.975]
----------------------------------------------------------------------------
---------
G1                   -3.3392      0.203    -16.466      0.000      -3.737
-2.942
failures              0.1566      0.120      1.305      0.192      -0.079
0.392
studytime            -0.0953      0.102     -0.931      0.352      -0.296
0.105
absences             -0.0119      0.100     -0.119      0.905      -0.207
0.184
Parental_Support     -0.1116      0.104     -1.069      0.285      -0.316
0.093
Distraction_Index     0.2090      0.109      1.918      0.055      -0.005
0.423
internet             -0.1754      0.104     -1.682      0.093      -0.380
0.029
1/2                  -4.8460      0.294    -16.496      0.000      -5.422
-4.270
2/3                   0.9446      0.097      9.716      0.000       0.754
1.135
3/4                   0.9175      0.088     10.474      0.000       0.746
1.089
4/5                   1.3036      0.077     16.892      0.000       1.152
1.455
============================================================================
=========
Ordinal Logistic Regression Accuracy: 0.1641

Feature importance for ordinal model:
G1: -3.3392
Distraction_Index: 0.2090
internet: -0.1754
failures: 0.1566
```

```
Parental_Support: -0.1116
studytime: -0.0953
absences: -0.0119
5-fold CV accuracy for ordinal logistic regression: 0.1834
```

```
/var/folders/gt/0gt4blm10_7d1j27s2crkgkc0000gn/T/ipykernel_93170/4027723963.
py:104: FutureWarning: Series.__getitem__ treating keys as positions is depr
ecated. In a future version, integer keys will always be treated as labels
(consistent with DataFrame behavior). To access a value by position, use `se
r.iloc[pos]`
  sorted_coefs = [coefs[i] for i in sort_idx]
/var/folders/gt/0gt4blm10_7d1j27s2crkgkc0000gn/T/ipykernel_93170/4027723963.
py:105: FutureWarning: Series.__getitem__ treating keys as positions is depr
ecated. In a future version, integer keys will always be treated as labels
(consistent with DataFrame behavior). To access a value by position, use `se
r.iloc[pos]`
  sorted_conf_low = [conf_int_low[i] for i in sort_idx]
/var/folders/gt/0gt4blm10_7d1j27s2crkgkc0000gn/T/ipykernel_93170/4027723963.
py:106: FutureWarning: Series.__getitem__ treating keys as positions is depr
ecated. In a future version, integer keys will always be treated as labels
(consistent with DataFrame behavior). To access a value by position, use `se
r.iloc[pos]`
  sorted_conf_high = [conf_int_high[i] for i in sort_idx]
```




```
<Figure size 1000x800 with 0 Axes>
```




```
Accuracy for Excellent: 1.0000
Accuracy for Very Good: 0.1905
Accuracy for Good: 0.2766
Accuracy for Sufficient: 0.1290
Accuracy for Fail: 0.0000
Excellent: Precision = 0.1750, Recall = 0.2258
Very Good: Precision = 0.1143, Recall = 0.1379
Good: Precision = 0.2097, Recall = 0.2766
Sufficient: Precision = 0.3077, Recall = 0.1290
Fail: Precision = 0.0000, Recall = 0.0000
```

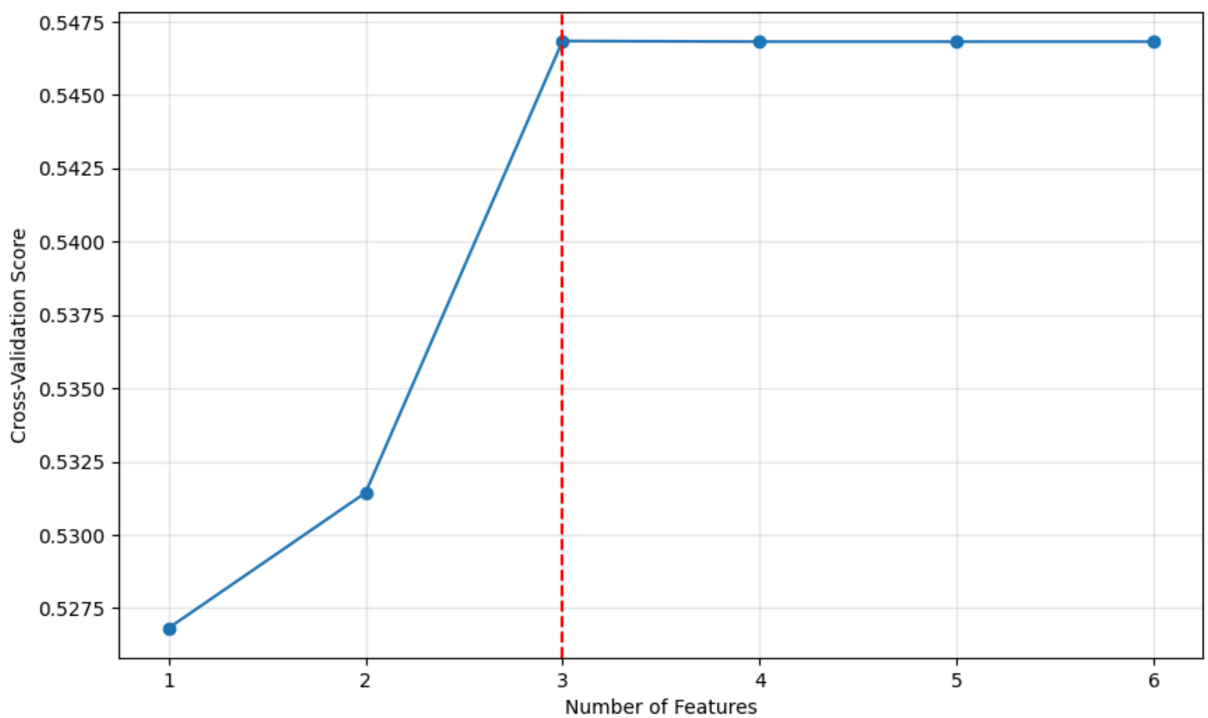
```
/Users/harshgandhi/opt/anaconda3/envs/new_env/lib/python3.9/site-packages/sk
learn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is
ill-defined and being set to 0.0 in labels with no predicted samples. Use `z
ero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

In [47]:

```
familyFeatures = [
    'Medu',
    'Fedu',
    'Pstatus',
    'famsup',
    'famrel',
    'famsize',
]

for feature in familyFeatures:
    if porData[feature].dtype == 'object':
        if porData[feature].nunique() == 2:
            porData[feature] = porData[feature].map(lambda x: 1 if x == 'yes
```

```python
xFamily = porData[familyFeatures]
yFamily = porData['passFail']
xFamTrainScaled, xFamTestScaled, yFamTrain, yFamTest, scalerFam = prepareDat


modelFam = LogisticRegression(max_iter=1000, class_weight='balanced')

rfeResults = {}

for numFeatures in range(1, len(familyFeatures) + 1):
    rfe = RFE(modelFam, n_features_to_select=numFeatures)
    rfe.fit(xFamTrainScaled, yFamTrain)

    selectedFeatures = [familyFeatures[i] for i, selected in enumerate(rfe.s

    cvScore = cross_val_score(modelFam, xFamily[selectedFeatures], yFamily,
    rfeResults[numFeatures] = {
        'features': selectedFeatures,
        'cv_score': cvScore
    }

    print(f"Number of features: {numFeatures}")
    print(f"Selected features: {selectedFeatures}")
    print(f"CV Score: {cvScore:.4f}\n")

bestNumFeatures = max(rfeResults, key=lambda x: rfeResults[x]['cv_score'])
bestFeatures = rfeResults[bestNumFeatures]['features']
bestScore = rfeResults[bestNumFeatures]['cv_score']

print(f"Best combination of family factors: {bestFeatures}")
print(f"CV Score with this combination: {bestScore:.4f}")

plt.figure(figsize=(10, 6))
numFeaturesList = list(rfeResults.keys())
cvScoresList = [rfeResults[n]['cv_score'] for n in numFeaturesList]

plt.plot(numFeaturesList, cvScoresList, marker='o')
plt.axvline(x=bestNumFeatures, color='r', linestyle='--')
plt.xlabel('Number of Features')
plt.ylabel('Cross-Validation Score')
plt.grid(True, alpha=0.3)
plt.show()
```

```
Number of features: 1
Selected features: ['Medu']
CV Score: 0.5268

Number of features: 2
Selected features: ['Medu', 'Fedu']
CV Score: 0.5314

Number of features: 3
Selected features: ['Medu', 'Fedu', 'famsup']
CV Score: 0.5468

Number of features: 4
Selected features: ['Medu', 'Fedu', 'famsup', 'famrel']
CV Score: 0.5468

Number of features: 5
Selected features: ['Medu', 'Fedu', 'famsup', 'famrel', 'famsize']
CV Score: 0.5468

Number of features: 6
Selected features: ['Medu', 'Fedu', 'Pstatus', 'famsup', 'famrel', 'famsiz
e']
CV Score: 0.5468

Best combination of family factors: ['Medu', 'Fedu', 'famsup']
CV Score with this combination: 0.5468
```

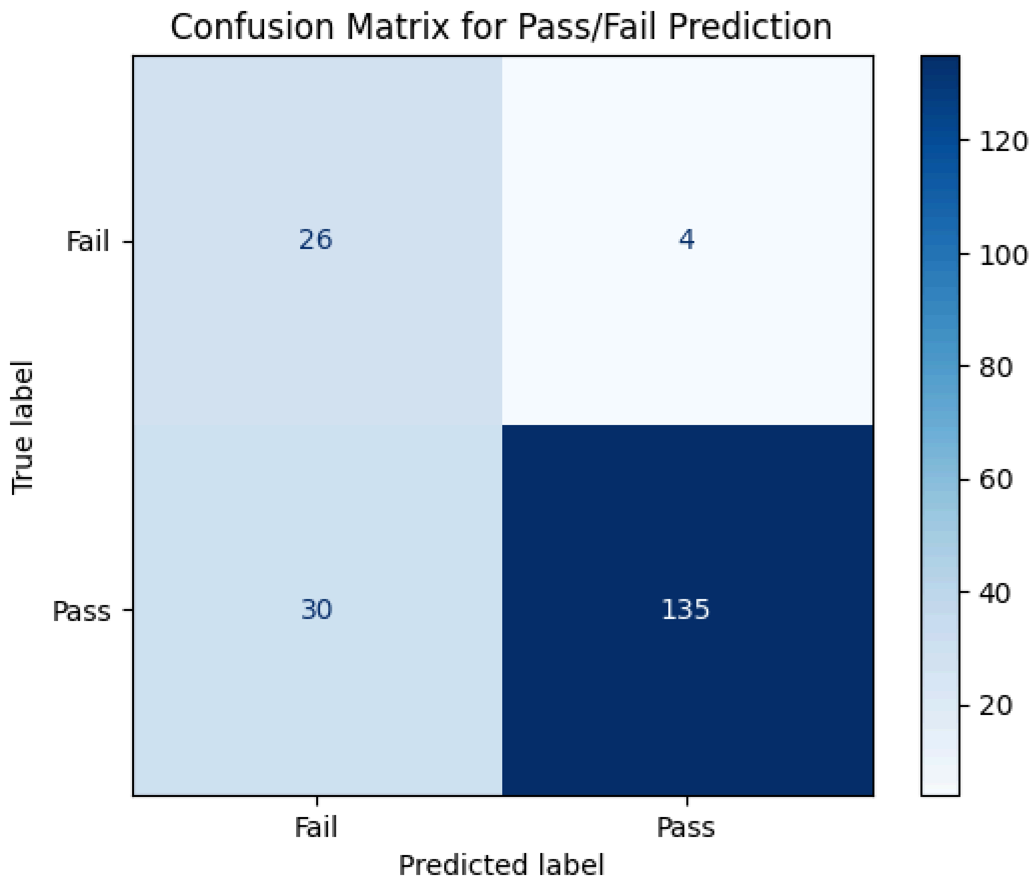


In [55]:
```
binaryFeatures = [
    'G1',
    'failures',
    'studytime',
    'absences',
    'Medu',
```

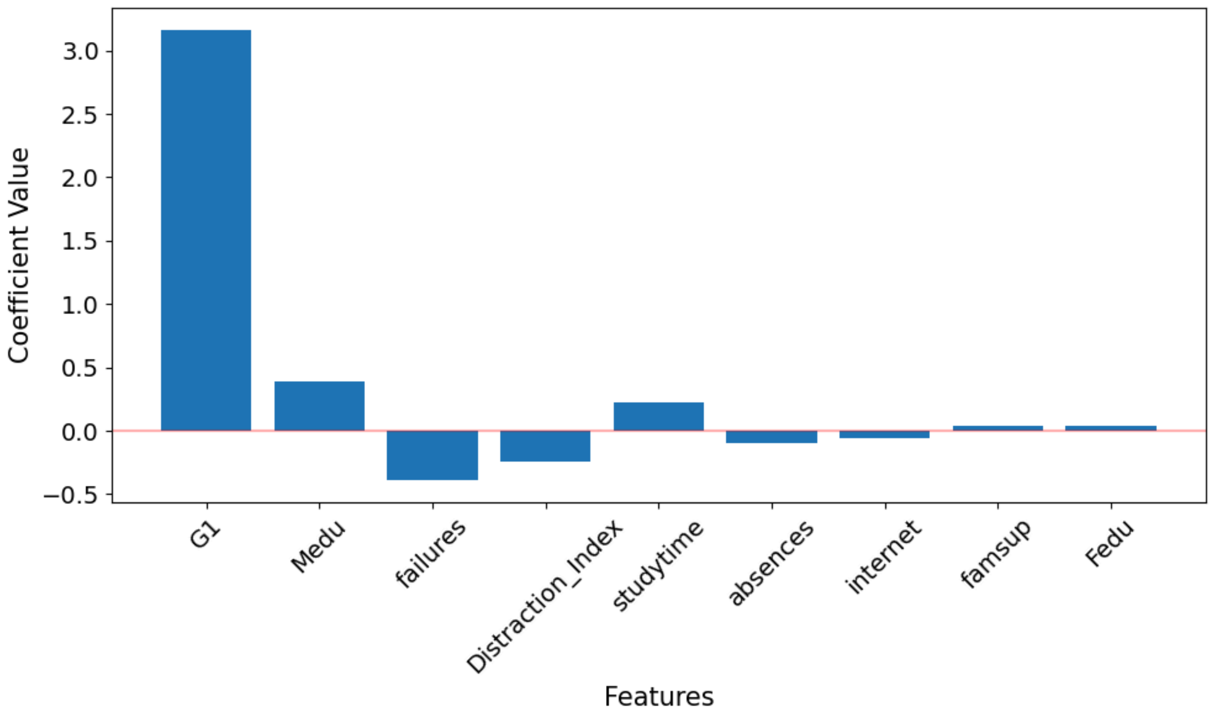
```
    'Fedu',
    'famsup',
    'Distraction_Index',
    'internet'
]

xBin = porData[binaryFeatures]
yBin = porData['passFail']
xBinTrainScaled, xBinTestScaled, yBinTrain, yBinTest, scalerBin = prepareDat


modelBin = LogisticRegression(max_iter=1000, class_weight='balanced')
modelBin.fit(xBinTrainScaled, yBinTrain)

yBinPred = modelBin.predict(xBinTestScaled)
yBinPredProba = modelBin.predict_proba(xBinTestScaled)[:, 1]

accuracyBin = accuracy_score(yBinTest, yBinPred)
print(f"\nBinary Classification Results:")
print(f"Accuracy: {accuracyBin:.4f}")

print("\nClassification Report:")
print(classification_report(yBinTest, yBinPred, target_names=['Fail', 'Pass'

cmBin = confusion_matrix(yBinTest, yBinPred)
print("\nConfusion Matrix:")
print(cmBin)

plt.figure(figsize=(8, 6))
disp = ConfusionMatrixDisplay(confusion_matrix=cmBin, display_labels=['Fail'
disp.plot(cmap='Blues')
plt.title('Confusion Matrix for Pass/Fail Prediction')
plt.show()

featureImportanceBin = dict(zip(binaryFeatures, modelBin.coef_[0]))
print("\nFeature Importance for Pass/Fail Prediction:")

sortedImportanceBin = {k: v for k, v in sorted(featureImportanceBin.items(),
                    key=lambda item: abs(item[1]), reverse=True)}
for feature, coef in sortedImportanceBin.items():
    print(f"{feature}: {coef:.4f}")

plt.figure(figsize=(10, 6))

featuresSorted = sorted(featureImportanceBin.keys(),
                         key=lambda x: abs(featureImportanceBin[x]), reverse
values = [featureImportanceBin[feature] for feature in featuresSorted]

plt.bar(featuresSorted, values)
plt.axhline(y=0, color='r', linestyle='-', alpha=0.3)

plt.xlabel('Features', fontsize=15)
plt.ylabel('Coefficient Value', fontsize=15)

plt.xticks(rotation=45, fontsize=14)
plt.yticks(fontsize=14)
```

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


# Cross-validation
cvScoresBin = cross_val_score(modelBin, xBin, yBin, cv=5)
print(f"\n5-fold CV accuracy for binary model: {cvScoresBin.mean():.4f} (±{c

fpr, tpr, _ = roc_curve(yBinTest, yBinPredProba)
rocAuc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {rocA
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

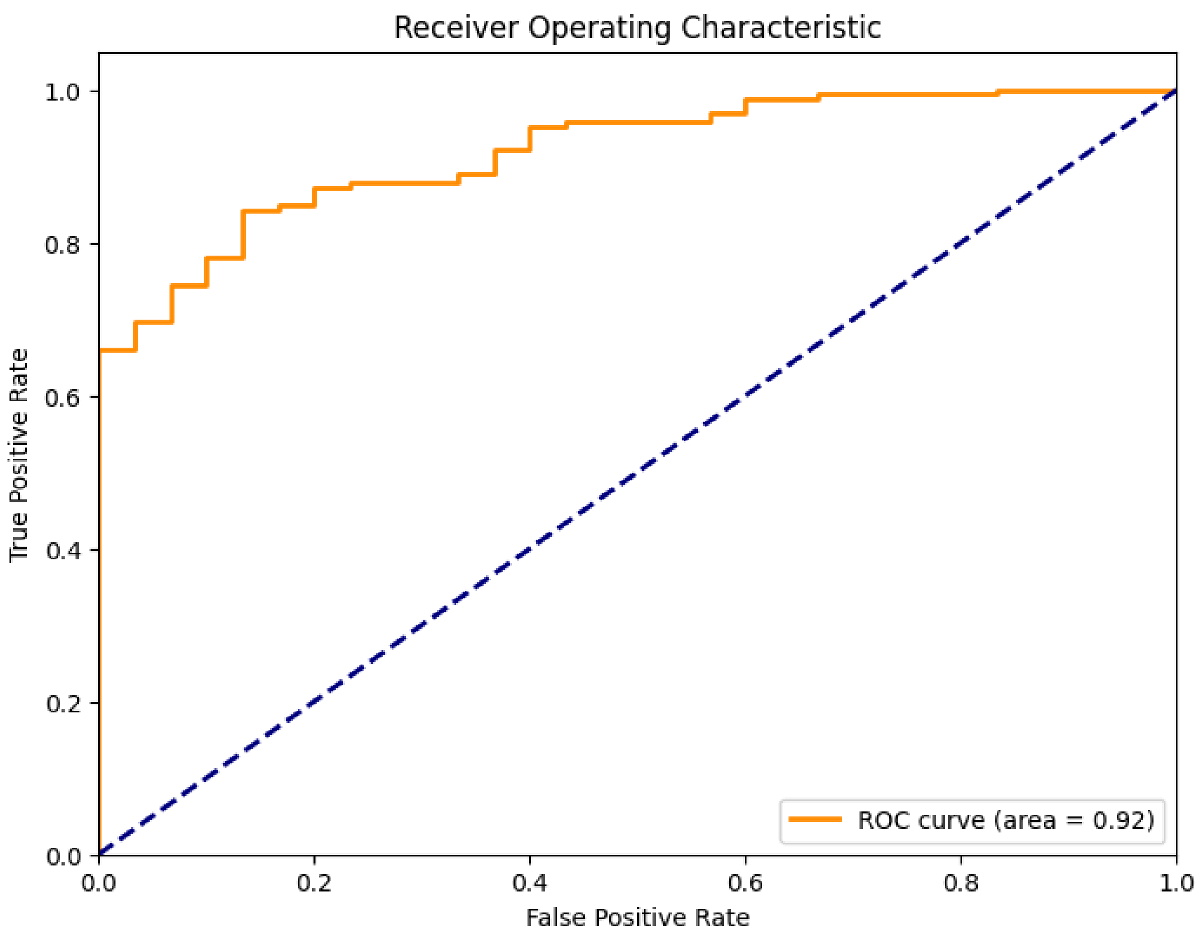
```
Binary Classification Results:
Accuracy: 0.8256

Classification Report:
              precision    recall  f1-score   support

        Fail       0.46      0.87      0.60        30
        Pass       0.97      0.82      0.89       165

    accuracy                           0.83       195
   macro avg       0.72      0.84      0.75       195
weighted avg       0.89      0.83      0.84       195


Confusion Matrix:
[[ 26   4]
 [ 30 135]]
<Figure size 800x600 with 0 Axes>
```




```
Feature Importance for Pass/Fail Prediction:
G1: 3.1604
Medu: 0.3868
failures: -0.3839
Distraction_Index: -0.2457
studytime: 0.2247
absences: -0.1008
internet: -0.0591
famsup: 0.0385
Fedu: 0.0364
```



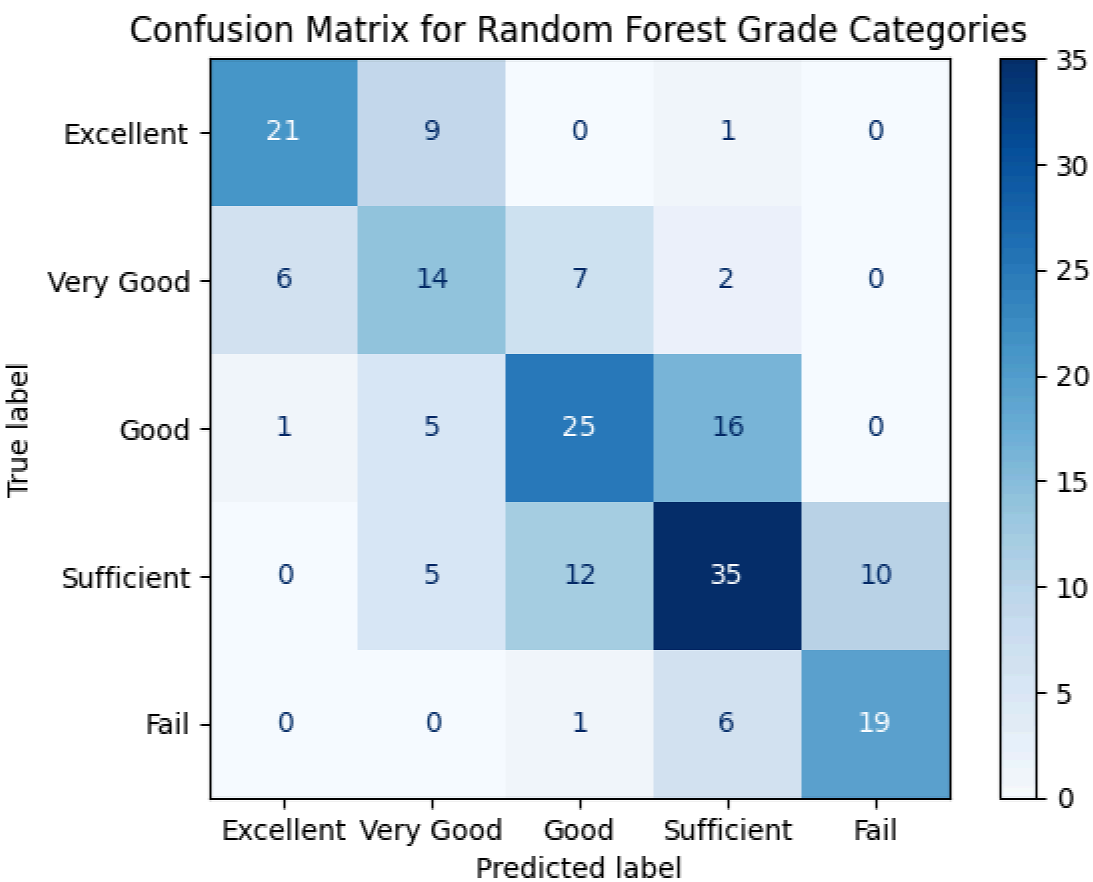

```
5-fold CV accuracy for binary model: 0.8566 (±0.0382)
```



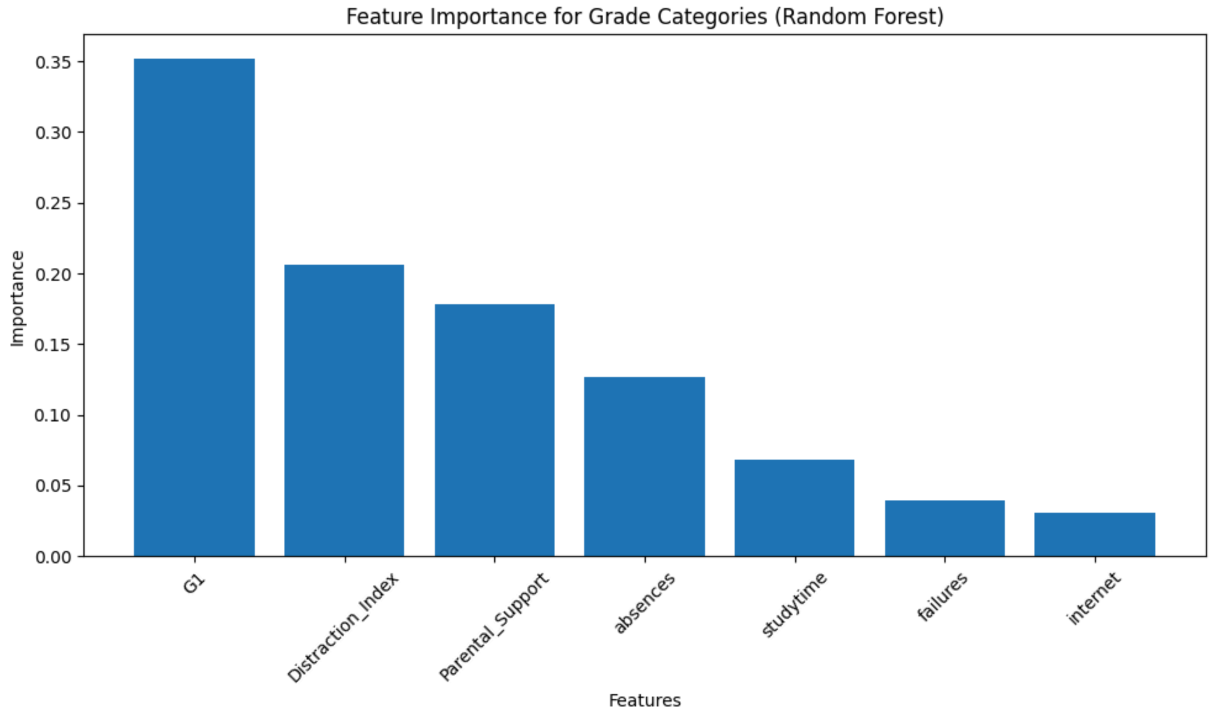
In [49]:
```
rfFeaturesOrd = ordinalFeatures

xRfOrd = porData[rfFeaturesOrd]
yRfOrd = porData['gradeCategory']
```

```
xRfOrdTrainScaled, xRfOrdTestScaled, yRfOrdTrain, yRfOrdTest, scalerRfOrd = 

rfModelOrd = RandomForestClassifier(n_estimators=100, random_state=42)
rfModelOrd.fit(xRfOrdTrainScaled, yRfOrdTrain)

yRfOrdPred = rfModelOrd.predict(xRfOrdTestScaled)

accuracyRfOrd = accuracy_score(yRfOrdTest, yRfOrdPred)
print("Random Forest for Grade Categories:")
print(f"Accuracy: {accuracyRfOrd:.4f}")

print("\nClassification Report:")
print(classification_report(yRfOrdTest, yRfOrdPred,
                            target_names=['Excellent', 'Very Good', 'Good', '


cmRfOrd = confusion_matrix(yRfOrdTest, yRfOrdPred)
print("\nConfusion Matrix:")
print(cmRfOrd)

plt.figure(figsize=(10, 8))
disp = ConfusionMatrixDisplay(confusion_matrix=cmRfOrd,
                              display_labels=['Excellent', 'Very Good', 'Goo
disp.plot(cmap='Blues')
plt.title('Confusion Matrix for Random Forest Grade Categories')
plt.show()

featureImportanceRfOrd = dict(zip(rfFeaturesOrd, rfModelOrd.feature_importan
print("\nFeature Importance for Grade Categories Prediction:")
sortedImportanceRfOrd = {k: v for k, v in sorted(featureImportanceRfOrd.item
                                               key=lambda item: item[1], rev
for feature, importance in sortedImportanceRfOrd.items():
    print(f"{feature}: {importance:.4f}")

plt.figure(figsize=(10, 6))
featuresSortedRfOrd = sorted(featureImportanceRfOrd.keys(),
                            key=lambda x: featureImportanceRfOrd[x], reverse=
valuesRfOrd = [featureImportanceRfOrd[feature] for feature in featuresSorted
plt.bar(featuresSortedRfOrd, valuesRfOrd)
plt.xlabel('Features')
plt.ylabel('Importance')
plt.title('Feature Importance for Grade Categories (Random Forest)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

cvScoresRfOrd = cross_val_score(RandomForestClassifier(n_estimators=100, ran
                               xRfOrd, yRfOrd, cv=5)
print(f"\n5-fold CV accuracy for Random Forest (grade categories): {cvScores
```

```
Random Forest for Grade Categories:
Accuracy: 0.5846

Classification Report:
              precision    recall  f1-score   support

   Excellent       0.75      0.68      0.71        31
   Very Good       0.42      0.48      0.45        29
        Good       0.56      0.53      0.54        47
  Sufficient       0.58      0.56      0.57        62
        Fail       0.66      0.73      0.69        26

    accuracy                           0.58       195
   macro avg       0.59      0.60      0.59       195
weighted avg       0.59      0.58      0.59       195


Confusion Matrix:
[[21  9  0  1  0]
 [ 6 14  7  2  0]
 [ 1  5 25 16  0]
 [ 0  5 12 35 10]
 [ 0  0  1  6 19]]
<Figure size 1000x800 with 0 Axes>
```



```
Feature Importance for Grade Categories Prediction:
G1: 0.3515
Distraction_Index: 0.2058
Parental_Support: 0.1785
absences: 0.1266
studytime: 0.0683
failures: 0.0390
internet: 0.0303
```

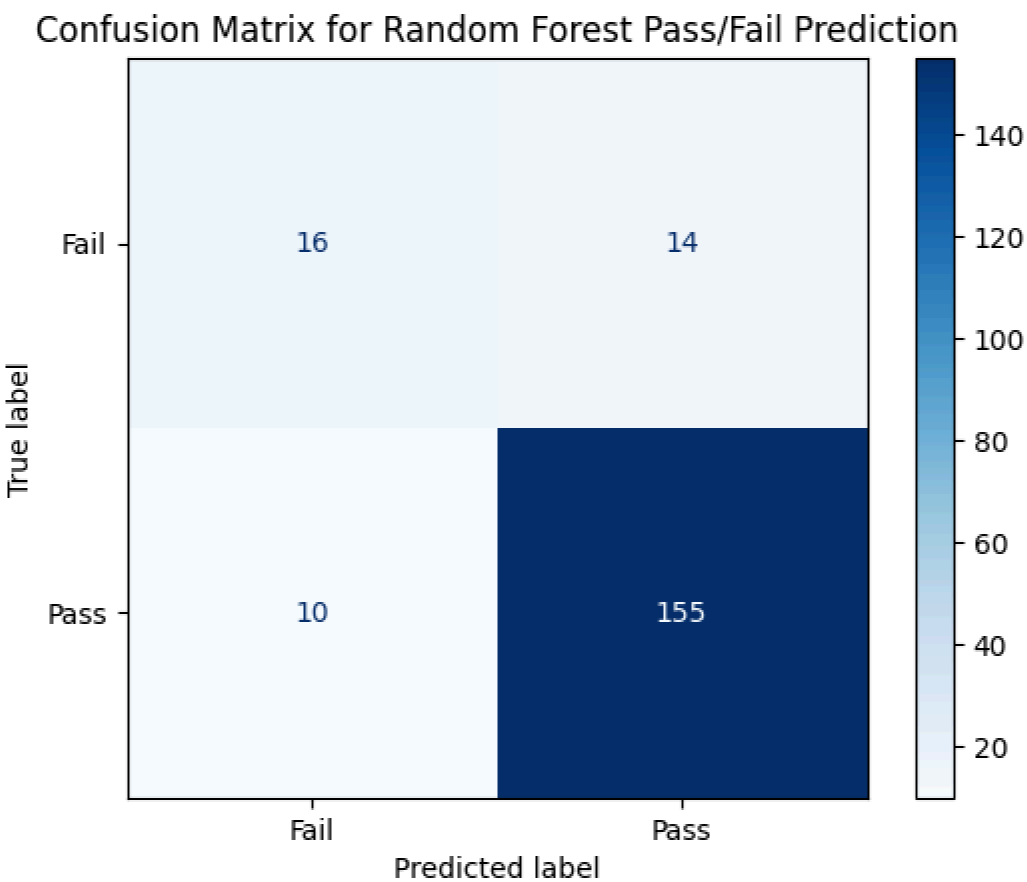



```
5-fold CV accuracy for Random Forest (grade categories): 0.5362 (±0.0207)
```

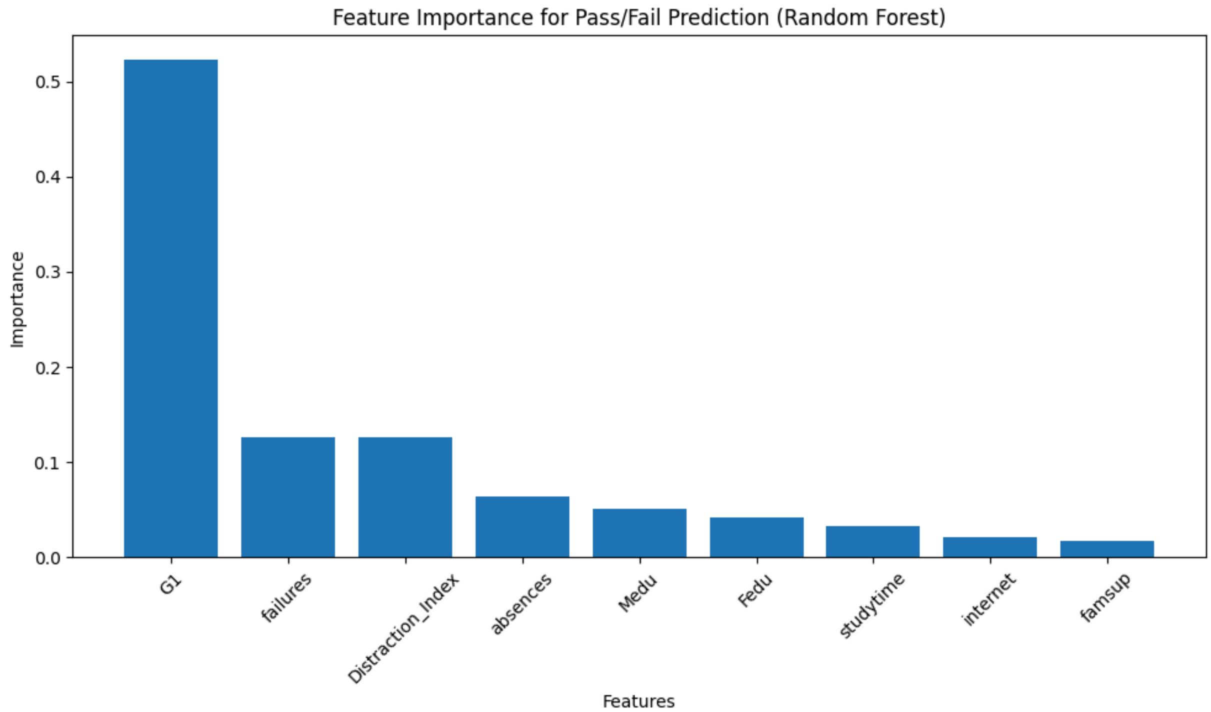
In [50]:
```
rfFeaturesBin = binaryFeatures

xRfBin = porData[rfFeaturesBin]
yRfBin = porData['passFail']
xRfBinTrainScaled, xRfBinTestScaled, yRfBinTrain, yRfBinTest, scalerRfBin = 

rfModelBin = RandomForestClassifier(n_estimators=100, class_weight='balanced
rfModelBin.fit(xRfBinTrainScaled, yRfBinTrain)

yRfBinPred = rfModelBin.predict(xRfBinTestScaled)
yRfBinPredProba = rfModelBin.predict_proba(xRfBinTestScaled)[:, 1]

accuracyRfBin = accuracy_score(yRfBinTest, yRfBinPred)
print("\nRandom Forest for Pass/Fail Prediction:")
print(f"Accuracy: {accuracyRfBin:.4f}")

print("\nClassification Report:")
print(classification_report(yRfBinTest, yRfBinPred, target_names=['Fail', 'P

cmRfBin = confusion_matrix(yRfBinTest, yRfBinPred)
print("\nConfusion Matrix:")
print(cmRfBin)

plt.figure(figsize=(8, 6))
```

```
disp = ConfusionMatrixDisplay(confusion_matrix=cmRfBin, display_labels=['Fai
disp.plot(cmap='Blues')
plt.title('Confusion Matrix for Random Forest Pass/Fail Prediction')
plt.show()

featureImportanceRfBin = dict(zip(rfFeaturesBin, rfModelBin.feature_importar
print("\nFeature Importance for Pass/Fail Prediction:")
sortedImportanceRfBin = {k: v for k, v in sorted(featureImportanceRfBin.item
                                               key=lambda item: item[1], rev
for feature, importance in sortedImportanceRfBin.items():
    print(f"{feature}: {importance:.4f}")

plt.figure(figsize=(10, 6))
featuresSortedRfBin = sorted(featureImportanceRfBin.keys(),
                           key=lambda x: featureImportanceRfBin[x], reverse=
valuesRfBin = [featureImportanceRfBin[feature] for feature in featuresSortec
plt.bar(featuresSortedRfBin, valuesRfBin)
plt.xlabel('Features')
plt.ylabel('Importance')
plt.title('Feature Importance for Pass/Fail Prediction (Random Forest)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

cvScoresRfBin = cross_val_score(RandomForestClassifier(n_estimators=100, cla
                               xRfBin, yRfBin, cv=5)
print(f"\n5-fold CV accuracy for Random Forest (pass/fail): {cvScoresRfBin.m

fprRf, tprRf, _ = roc_curve(yRfBinTest, yRfBinPredProba)
rocAucRf = auc(fprRf, tprRf)

plt.figure(figsize=(8, 6))
plt.plot(fprRf, tprRf, color='darkorange', lw=2, label=f'RF ROC curve (area
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - Random Forest')
plt.legend(loc="lower right")
plt.show()
```

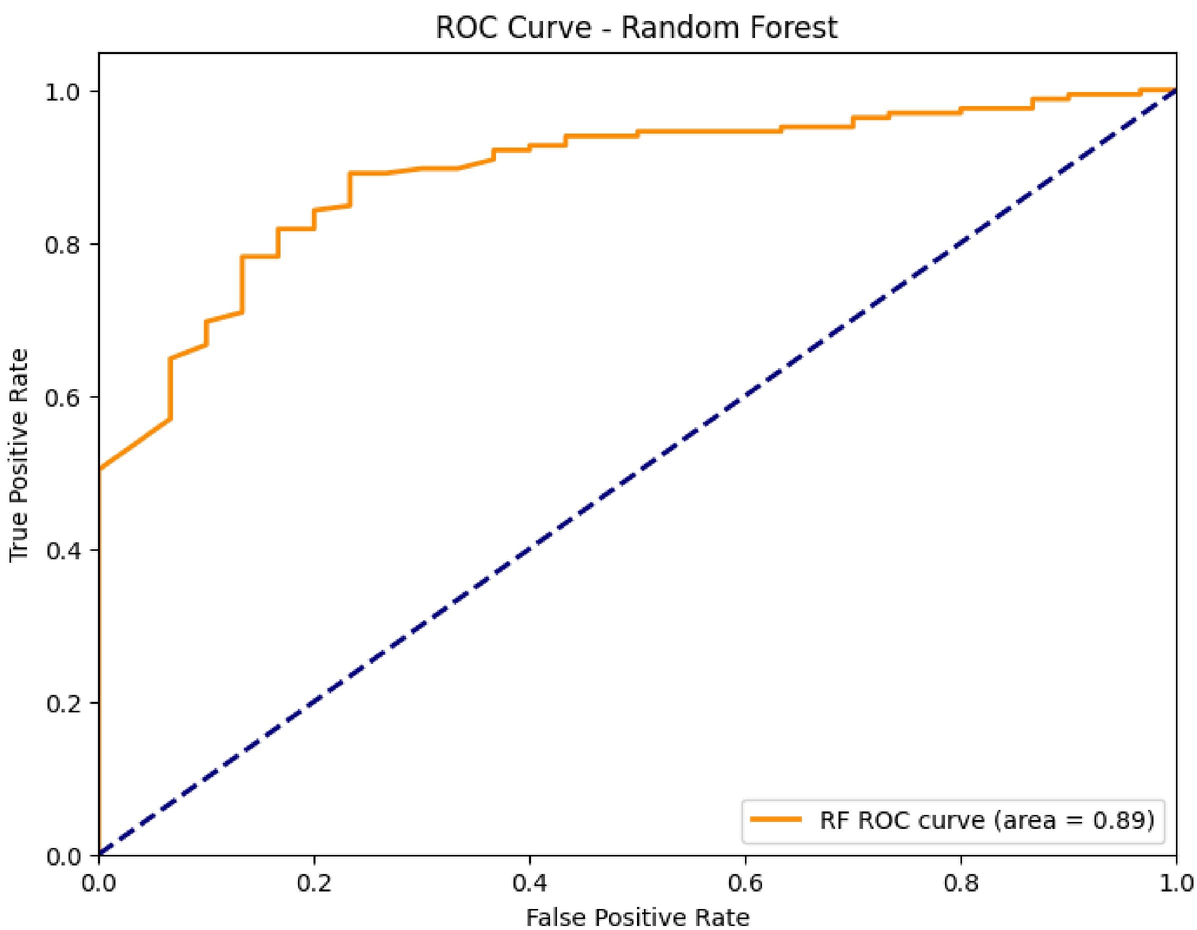
```
Random Forest for Pass/Fail Prediction:
Accuracy: 0.8769

Classification Report:
              precision    recall  f1-score   support

        Fail       0.62      0.53      0.57        30
        Pass       0.92      0.94      0.93       165

    accuracy                           0.88       195
   macro avg       0.77      0.74      0.75       195
weighted avg       0.87      0.88      0.87       195


Confusion Matrix:
[[ 16  14]
 [ 10 155]]
<Figure size 800x600 with 0 Axes>
```




```
Feature Importance for Pass/Fail Prediction:
G1: 0.5225
failures: 0.1265
Distraction_Index: 0.1257
absences: 0.0638
Medu: 0.0502
Fedu: 0.0418
studytime: 0.0320
internet: 0.0206
famsup: 0.0170
```



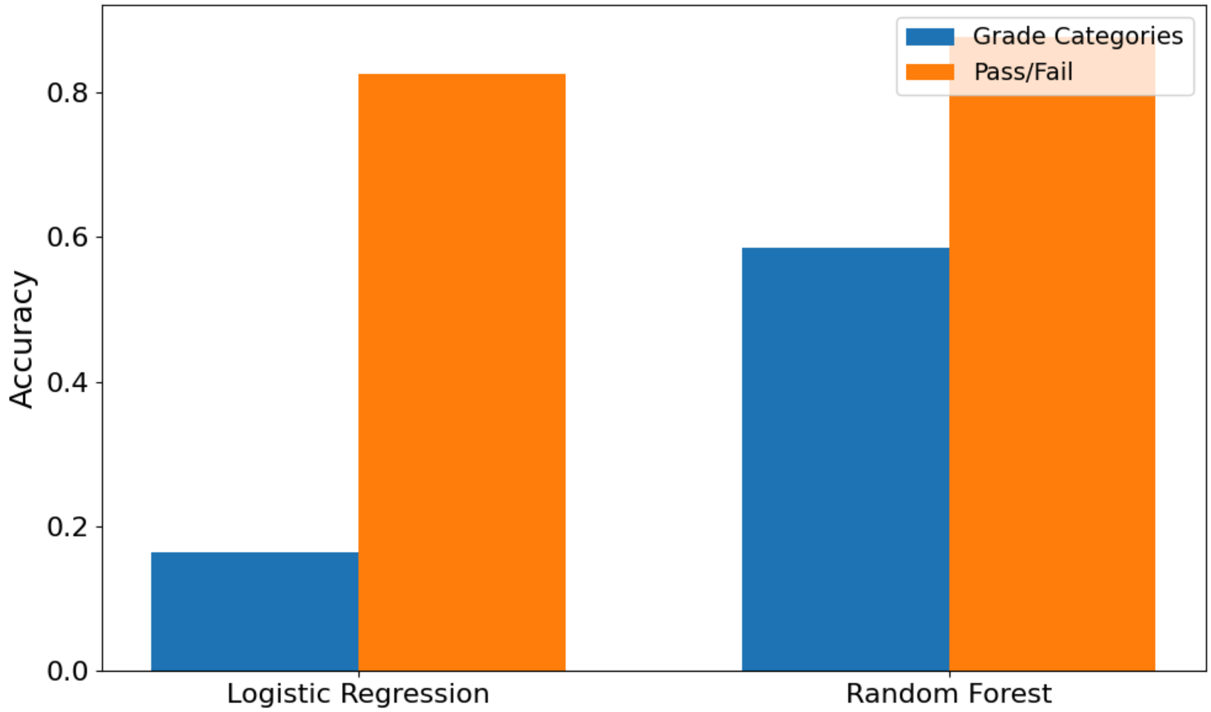

```
5-fold CV accuracy for Random Forest (pass/fail): 0.8859 (±0.0329)
```



In [53]:
```
print("\nModel Comparison - Grade Categories:")
print(f"Logistic Regression - Average Accuracy: {avgAccuracy:.4f}")
print(f"Random Forest - Accuracy: {accuracyRfOrd:.4f}")
print(f"Logistic Regression - CV Accuracy: {np.mean(cvScores):.4f}")
```

```
print(f"Random Forest - CV Accuracy: {cvScoresRfOrd.mean():.4f}")

print("\nModel Comparison - Pass/Fail Prediction:")
print(f"Logistic Regression - Accuracy: {accuracyBin:.4f}")
print(f"Random Forest - Accuracy: {accuracyRfBin:.4f}")
print(f"Logistic Regression - CV Accuracy: {cvScoresBin.mean():.4f}")
print(f"Random Forest - CV Accuracy: {cvScoresRfBin.mean():.4f}")

plt.figure(figsize=(10, 6))

models = ['Logistic Regression', 'Random Forest']
accuracies_categories = [avgAccuracy, accuracyRfOrd]
accuracies_passfail = [accuracyBin, accuracyRfBin]

x = np.arange(len(models))
width = 0.35

plt.bar(x - width/2, accuracies_categories, width, label='Grade Categories')
plt.bar(x + width/2, accuracies_passfail, width, label='Pass/Fail')

plt.ylabel('Accuracy', fontsize=18)
plt.xticks(x, models, fontsize=16)
plt.yticks(fontsize=16)
plt.legend(fontsize=14)

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

```
Model Comparison - Grade Categories:
Logistic Regression - Average Accuracy: 0.1641
Random Forest - Accuracy: 0.5846
Logistic Regression - CV Accuracy: 0.1834
Random Forest - CV Accuracy: 0.5362

Model Comparison - Pass/Fail Prediction:
Logistic Regression - Accuracy: 0.8256
Random Forest - Accuracy: 0.8769
Logistic Regression - CV Accuracy: 0.8566
Random Forest - CV Accuracy: 0.8859
```


Grade Categories
Pass/Fail
0.8
0.6
0.4
0.2
0.0
Accuracy
Logistic Regression
Random Forest

```
In [ ]:
```