Conflict & Adaptation Analysis

How Conflict Handling Relates to Team Outcomes

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

plt.style.use('seaborn-v0_8-whitegrid')
plt.rcParams['figure.figsize'] = (10, 6)
plt.rcParams['font.size'] = 11

# Load data
df = pd.read_excel('SurveyData211.xlsx')

# Key variables
OUTCOME_VARS = ['GO1', 'NPS1', 'NPS2', 'SE1', 'SE2', 'RLS1']
VAR_LABELS = {
    'CA1': 'Conflict Adaptation (1-10)',
    'GO1': 'Growth/Outcomes (1-5)',
    'NPS1': 'Team Satisfaction 1 (1-5)',
    'NPS2': 'Team Satisfaction 2 (1-5)',
    'SE1': 'Self-Efficacy 1 (1-5)',
    'SE2': 'Self-Efficacy 2 (1-5)',
    'RLS1': 'Relationship Strength (1-10)',
    'Section': 'Class Section'
}

print(f"Dataset: {df.shape[0]} responses, {df.shape[1]} variables")
```

```
Dataset: 210 responses, 27 variables
```

. Distribution of Conflict Adaptation Scores

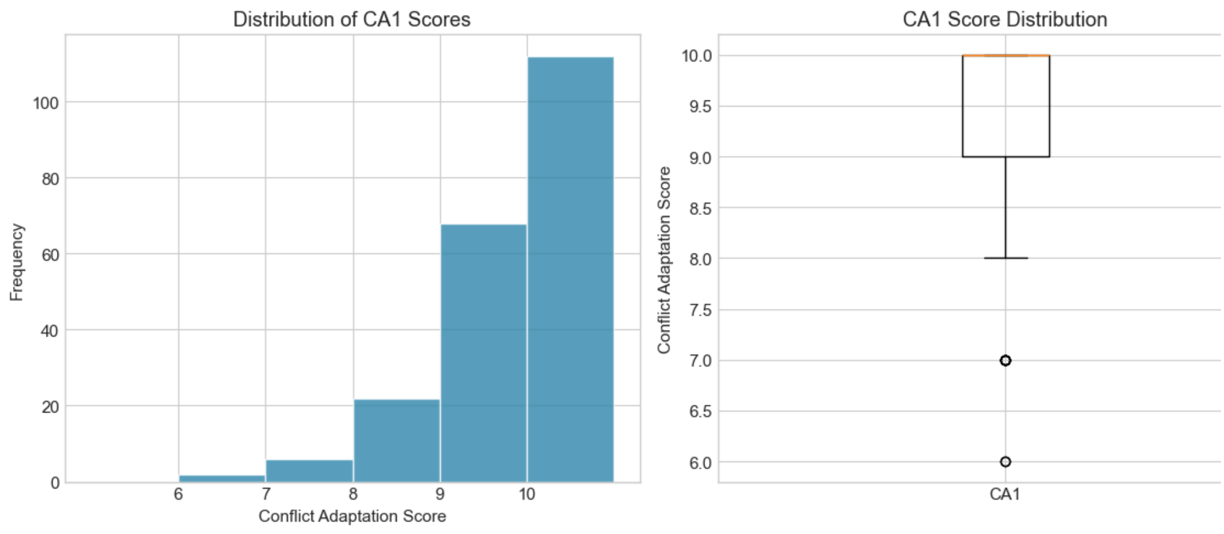
In [2]:
```
# Summary statistics for CA1 and outcome variables
summary_vars = ['CA1'] + OUTCOME_VARS
summary_stats = df[summary_vars].describe().round(2)
summary_stats
```

Out[2]:

	CA	GO	NPS	NPS	SE	SE	RLS
count	.	.	.	.	.	.	.
mean	.	.	.	.	.	.	.
std	.	.	.	.	.	.	.
min	.	.	.	.	.	.	.
%	.	.	.	.	.	.	.
%	.	.	.	.	.	.	.
%	.	.	.	.	.	.	.
max	.	.	.	.	.	.	.

In [3]:

```
# Figure 1: Distribution of Conflict Adaptation Scores
fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# Histogram
axes[0].hist(df['CA1'].dropna(), bins=range(5, 12), edgecolor='white', co
axes[0].set_xlabel('Conflict Adaptation Score')
axes[0].set_ylabel('Frequency')
axes[0].set_title('Distribution of CA1 Scores')
axes[0].set_xticks(range(6, 11))

# Box plot
axes[1].boxplot(df['CA1'].dropna(), vert=True)
axes[1].set_ylabel('Conflict Adaptation Score')
axes[1].set_title('CA1 Score Distribution')
axes[1].set_xticklabels(['CA1'])

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

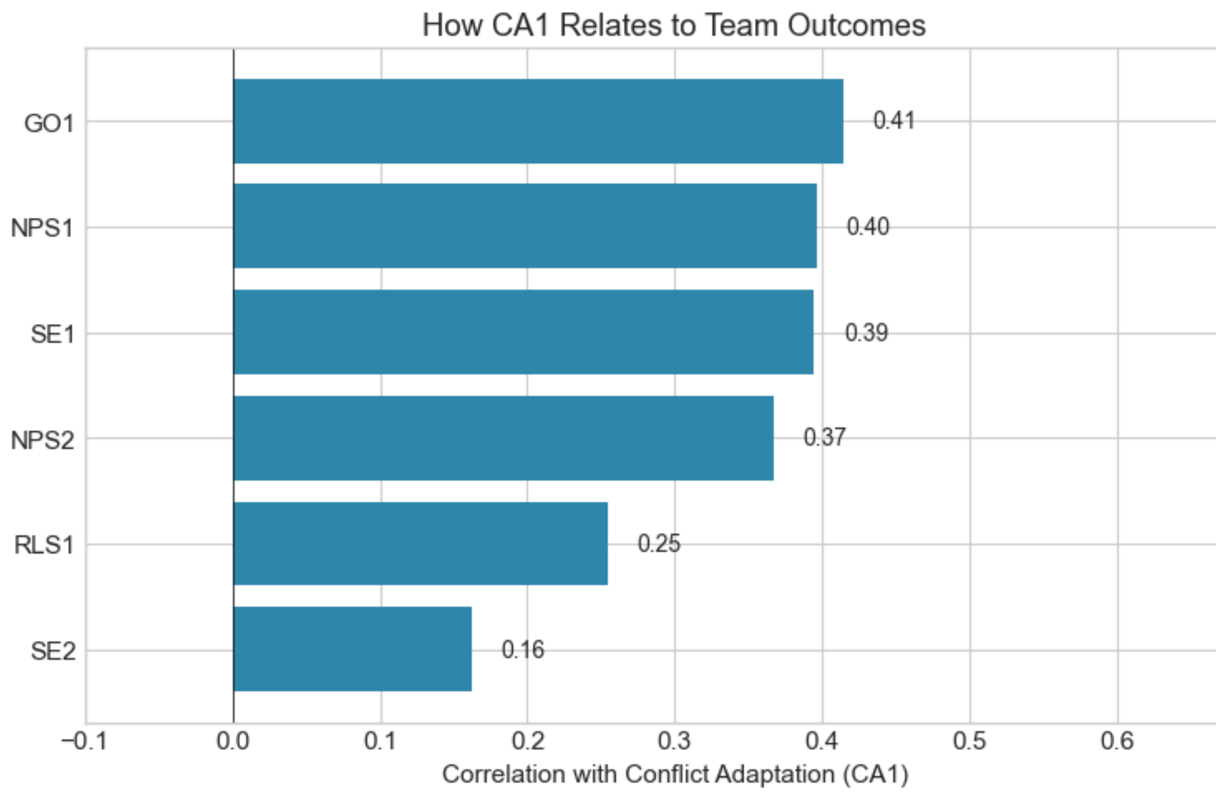


. Correlation Analysis: CA vs Outcome Variables

In [4]:

```
# Correlation analysis
corr_vars = ['CA1'] + OUTCOME_VARS
corr_matrix = df[corr_vars].corr().round(3)
```

```
# Figure 2: Simple bar chart of CA1 correlations
ca_corrs = corr_matrix['CA1'].drop('CA1').sort_values(ascending=True)

fig, ax = plt.subplots(figsize=(8, 5))
colors = ['#2E86AB' if r > 0 else '#E94F37' for r in ca_corrs.values]
bars = ax.barh(ca_corrs.index, ca_corrs.values, color=colors)
ax.set_xlabel('Correlation with Conflict Adaptation (CA1)')
ax.set_title('How CA1 Relates to Team Outcomes')
ax.axvline(x=0, color='black', linewidth=0.5)
ax.set_xlim(-0.1, 0.7)

# Add value labels
for bar, val in zip(bars, ca_corrs.values):
    ax.text(val + 0.02, bar.get_y() + bar.get_height()/2, f'{val:.2f}', v

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



```
In [5]: # Table: CA1 correlations with outcome variables
        ca_corrs = corr_matrix['CA1'].drop('CA1').sort_values(ascending=False)
        corr_table = pd.DataFrame({
            'Variable': ca_corrs.index,
            'Correlation with CA1': ca_corrs.values,
            'Interpretation': ['Strong positive' if abs(r) > 0.5 else 'Moderate p
                               else 'Weak positive' if r > 0 else 'Weak negative'
        })
        corr_table
```

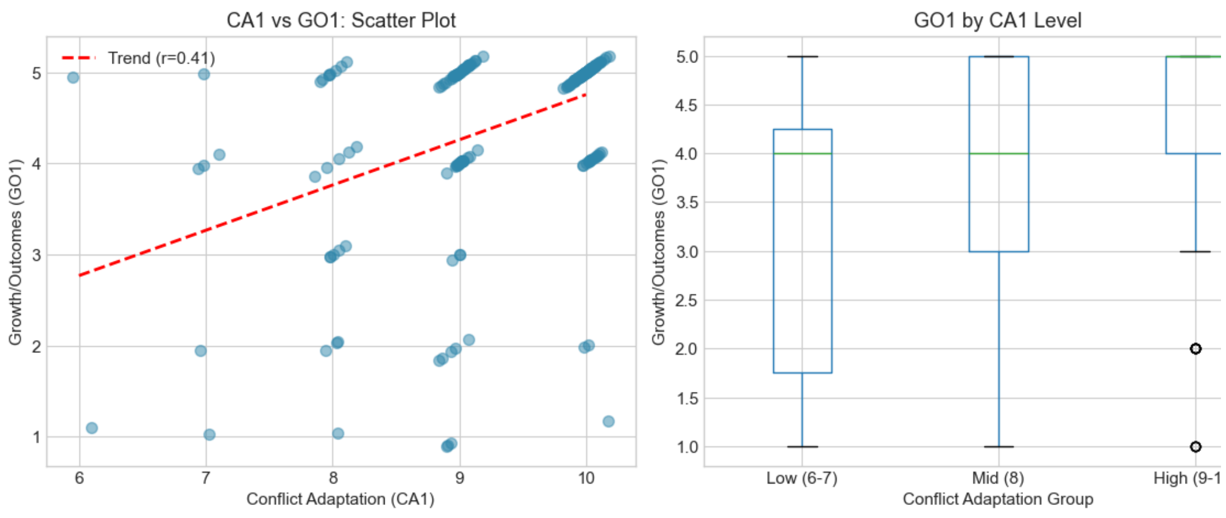
Out[5]:

Variable	Correlation with CA	Interpretation
GO	.	Moderate positive
NPS	.	Moderate positive
SE	.	Moderate positive
NPS	.	Moderate positive
RLS	.	Weak positive
SE	.	Weak positive

. CA vs Outcome Variables: Detailed Relationship

In [6]:

```
# Figure 3: CA1 vs Growth/Outcomes (GO1)
fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# Scatter with jitter
jitter = np.random.normal(0, 0.08, len(df))
axes[0].scatter(df['CA1'] + jitter, df['GO1'] + jitter, alpha=0.5, c='#2E
z = np.polyfit(df['CA1'].dropna(), df.loc[df['CA1'].notna(), 'GO1'], 1)
p = np.poly1d(z)
x_line = np.linspace(df['CA1'].min(), df['CA1'].max(), 100)
axes[0].plot(x_line, p(x_line), 'r--', linewidth=2, label=f'Trend (r={cor
axes[0].set_xlabel('Conflict Adaptation (CA1)')
axes[0].set_ylabel('Growth/Outcomes (GO1)')
axes[0].set_title('CA1 vs GO1: Scatter Plot')
axes[0].legend()

# Box plot by CA1 groups
df['CA1_group'] = pd.cut(df['CA1'], bins=[5, 7, 8, 10], labels=['Low (6-7
df.boxplot(column='GO1', by='CA1_group', ax=axes[1])
axes[1].set_xlabel('Conflict Adaptation Group')
axes[1].set_ylabel('Growth/Outcomes (GO1)')
axes[1].set_title('GO1 by CA1 Level')
plt.suptitle('')

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



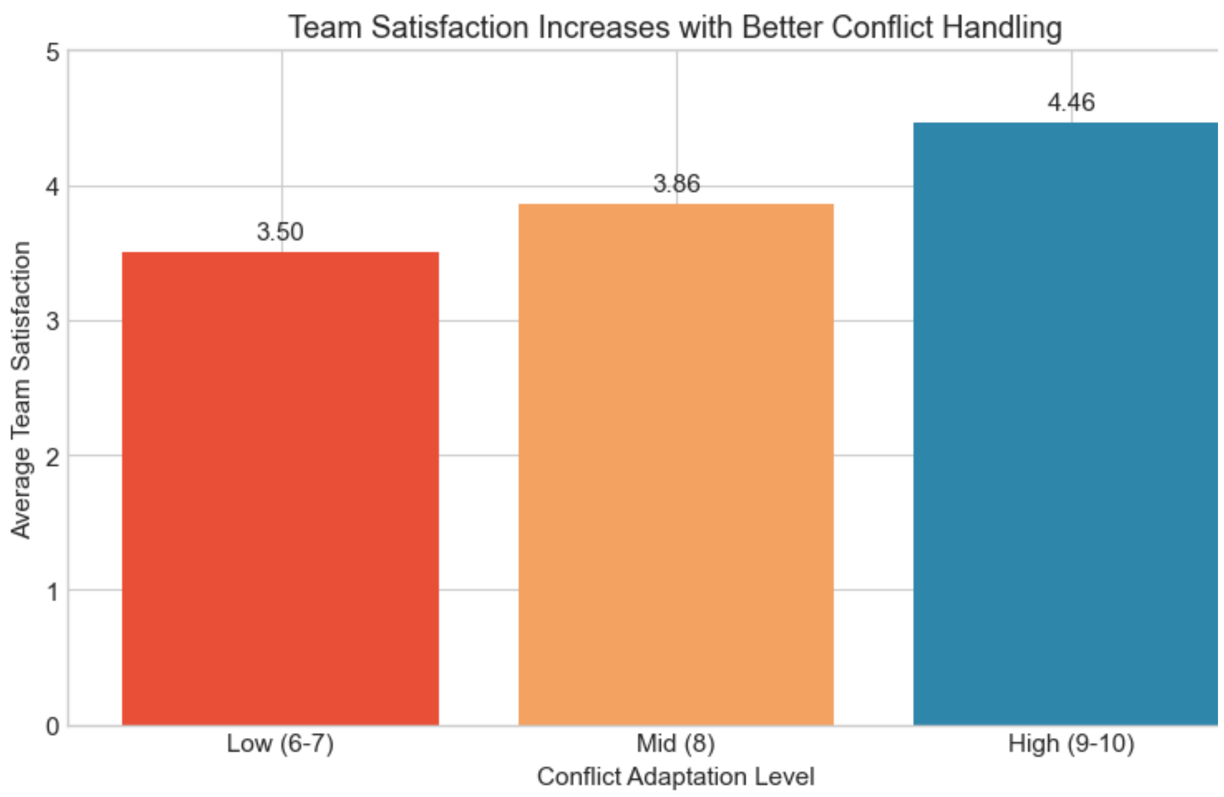
In [7]:

```python
# Table: Team Satisfaction by CA1 Level
nps_by_group = df.groupby('CA1_group')['NPS1'].agg(['mean', 'count']).rou
nps_by_group.columns = ['Avg Satisfaction', 'N']
print("Team Satisfaction (NPS1) by Conflict Adaptation Level:")
display(nps_by_group)

# Figure 4: Simple bar - Satisfaction by CA1 level
fig, ax = plt.subplots(figsize=(8, 5))
groups = ['Low (6-7)', 'Mid (8)', 'High (9-10)']
nps_means = [nps_by_group.loc[g, 'Avg Satisfaction'] if g in nps_by_group

bars = ax.bar(groups, nps_means, color=['#E94F37', '#F4A261', '#2E86AB'])
ax.set_xlabel('Conflict Adaptation Level')
ax.set_ylabel('Average Team Satisfaction')
ax.set_title('Team Satisfaction Increases with Better Conflict Handling')
ax.set_ylim(0, 5)

for bar in bars:
    ax.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.1,
            f'{bar.get_height():.2f}', ha='center', fontsize=11)

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

```
Team Satisfaction (NPS1) by Conflict Adaptation Level:
```

```
/var/folders/vp/5hvn916x1qz0gt_r5m3ynbl80000gn/T/ipykernel_56316/1700612482.p
FutureWarning: The default of observed=False is deprecated and will be change
True in a future version of pandas. Pass observed=False to retain current beh
or observed=True to adopt the future default and silence this warning.
  nps_by_group = df.groupby('CA1_group')['NPS1'].agg(['mean', 'count']).round
```

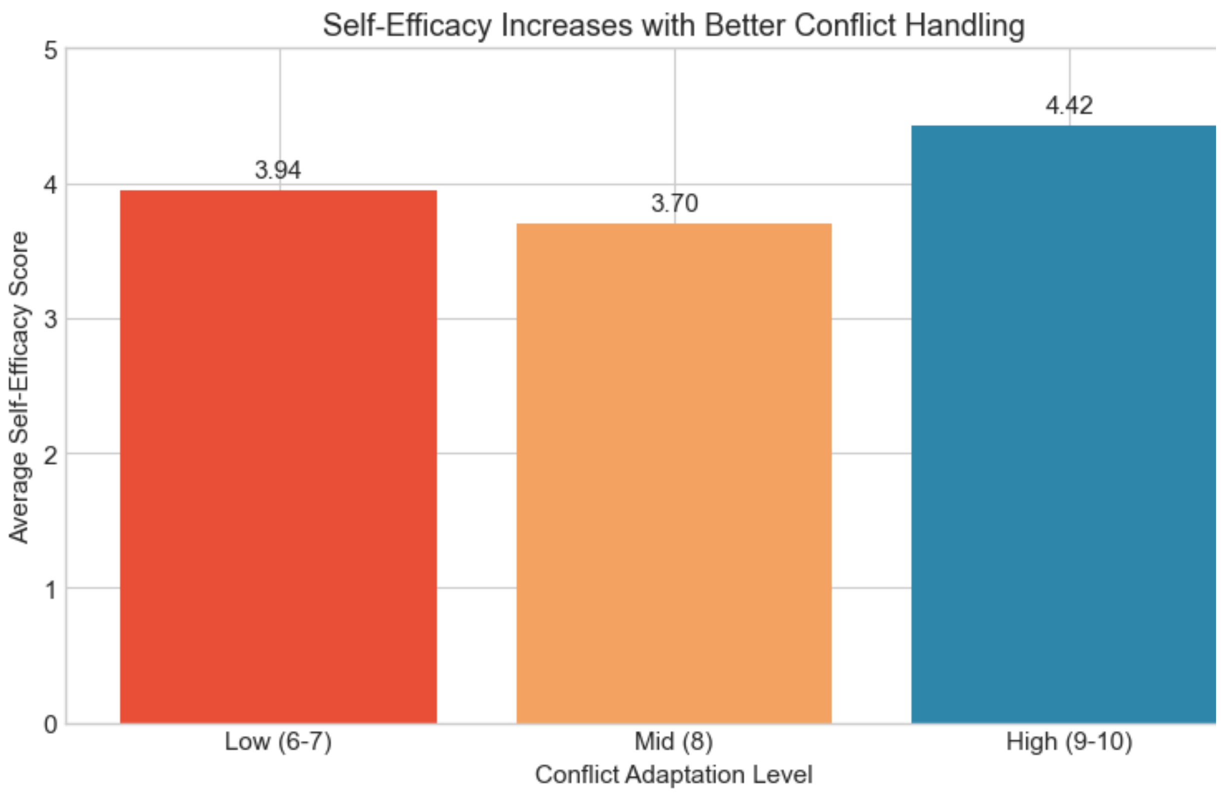
	Avg Satisfaction	N
CA _group		
Low (-)	.	
Mid ( )	.	
High (-)	.	



In [8]:
```
# Table: Self-Efficacy by CA1 Level
se_by_group = df.groupby('CA1_group')[['SE1', 'SE2']].mean().round(2)
se_by_group['SE Average'] = ((se_by_group['SE1'] + se_by_group['SE2']) /
print("Self-Efficacy Scores by Conflict Adaptation Level:")
display(se_by_group)

# Figure 5: Simple grouped bar – SE by CA1 level
fig, ax = plt.subplots(figsize=(8, 5))
groups = ['Low (6-7)', 'Mid (8)', 'High (9-10)']
se_means = [se_by_group.loc[g, 'SE Average'] if g in se_by_group.index el

bars = ax.bar(groups, se_means, color=['#E94F37', '#F4A261', '#2E86AB'])
ax.set_xlabel('Conflict Adaptation Level')
ax.set_ylabel('Average Self-Efficacy Score')
ax.set_title('Self-Efficacy Increases with Better Conflict Handling')
ax.set_ylim(0, 5)

for bar in bars:
    ax.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.1,
            f'{bar.get_height():.2f}', ha='center', fontsize=11)

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

```
Self-Efficacy Scores by Conflict Adaptation Level:
/var/folders/vp/5hvn916x1qz0gt_r5m3ynbl80000gn/T/ipykernel_56316/281562401.py
FutureWarning: The default of observed=False is deprecated and will be change
True in a future version of pandas. Pass observed=False to retain current beh
or observed=True to adopt the future default and silence this warning.
  se_by_group = df.groupby('CA1_group')[['SE1', 'SE2']].mean().round(2)
```

	SE	SE	SE Average
CA _group			
Low (-)	.	.	.
Mid ( )	.	.	.
High (-)	.	.	.

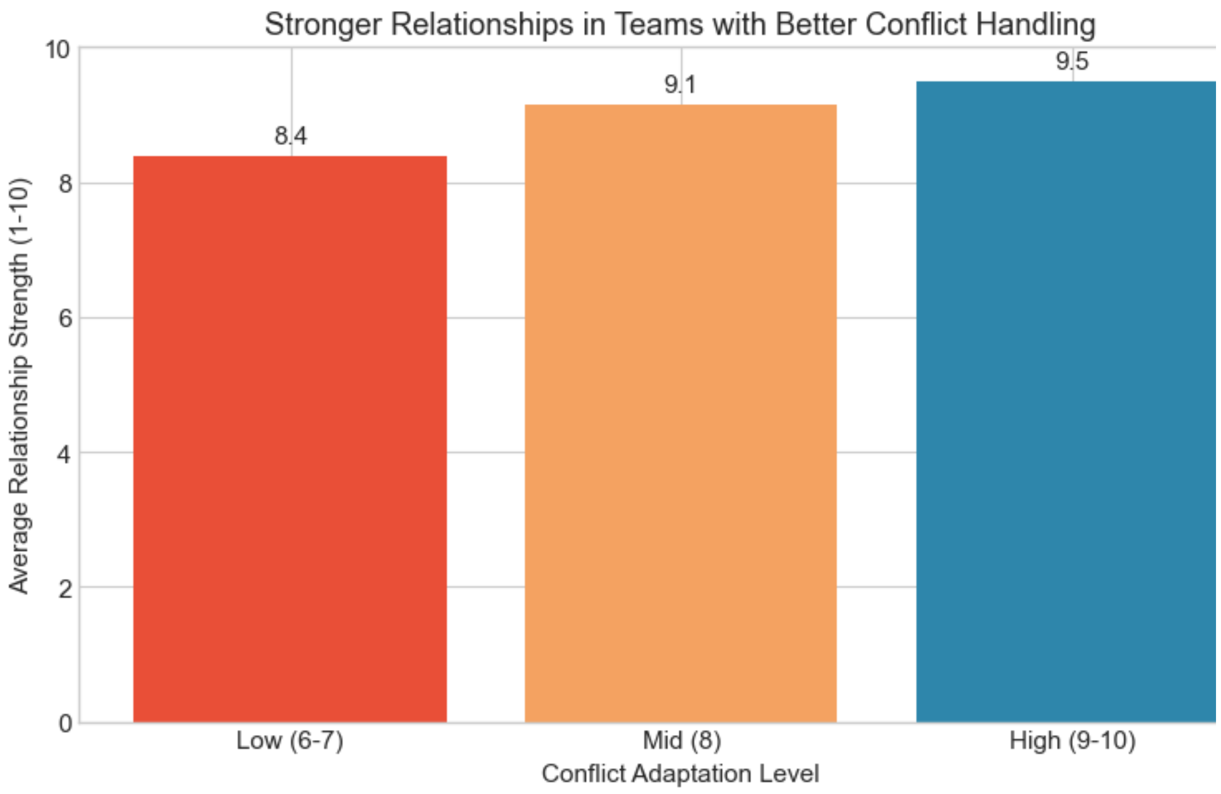


```
In [9]: # Table: Relationship Strength by CA1 Level
rls_by_group = df.groupby('CA1_group')['RLS1'].agg(['mean', 'count']).rou
rls_by_group.columns = ['Avg Relationship Strength', 'N']
print("Relationship Strength (RLS1) by Conflict Adaptation Level:")
display(rls_by_group)

# Figure 6: Simple bar – Relationship Strength by CA1 level
fig, ax = plt.subplots(figsize=(8, 5))
groups = ['Low (6–7)', 'Mid (8)', 'High (9–10)']
rls_means = [rls_by_group.loc[g, 'Avg Relationship Strength'] if g in rls

bars = ax.bar(groups, rls_means, color=['#E94F37', '#F4A261', '#2E86AB'])
ax.set_xlabel('Conflict Adaptation Level')
ax.set_ylabel('Average Relationship Strength (1–10)')
ax.set_title('Stronger Relationships in Teams with Better Conflict Handli
ax.set_ylim(0, 10)

for bar in bars:
    ax.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 0.2,
            f'{bar.get_height():.1f}', ha='center', fontsize=11)

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

```
Relationship Strength (RLS1) by Conflict Adaptation Level:
```

```
/var/folders/vp/5hvn916x1qz0gt_r5m3ynbl80000gn/T/ipykernel_56316/3062436781.p
FutureWarning: The default of observed=False is deprecated and will be change
True in a future version of pandas. Pass observed=False to retain current beh
or observed=True to adopt the future default and silence this warning.
  rls_by_group = df.groupby('CA1_group')['RLS1'].agg(['mean', 'count']).round
```

	Avg Relationship Strength	N
CA _group		
Low (-)	.	
Mid ( )	.	
High (-)	.	



. High vs Low Conflict Adaptation: Group Comparison

In [10]:
```python
# Split by median CA1 score
ca_median = df['CA1'].median()
df['CA1_binary'] = df['CA1'].apply(lambda x: 'High CA' if x >= ca_median

# Comparison table
comparison = df.groupby('CA1_binary')[OUTCOME_VARS].agg(['mean', 'std']).
comparison.columns = [f'{col[0]}_{col[1]}' for col in comparison.columns]

# Reshape for cleaner display
comparison_clean = pd.DataFrame({
    'Group': ['High CA (≥{:.0f})'.format(ca_median), 'Low CA (<{:.0f})'.f
    'N': [len(df[df['CA1_binary'] == 'High CA']), len(df[df['CA1_binary']
    'GO1 Mean': [comparison.loc['High CA', 'GO1_mean'], comparison.loc['L
    'NPS1 Mean': [comparison.loc['High CA', 'NPS1_mean'], comparison.loc[
    'SE1 Mean': [comparison.loc['High CA', 'SE1_mean'], comparison.loc['L
    'RLS1 Mean': [comparison.loc['High CA', 'RLS1_mean'], comparison.loc[
})
```

```
print(f"Median CA1 score: {ca_median}")
comparison_clean
```

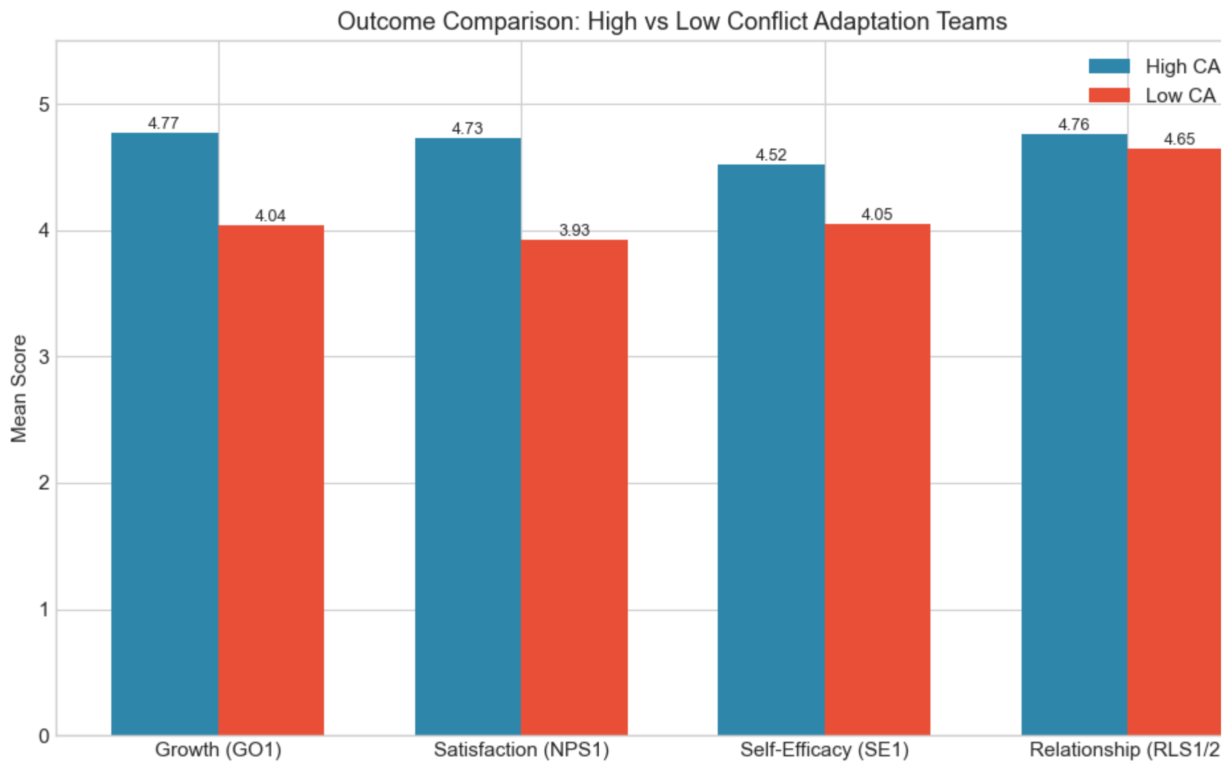
```
Median CA1 score: 10.0
```

Out[10]:

Group	N	GO	Mean	NPS	Mean	SE	Mean	RLS	Mean
High CA (≥)			.		.		.		.
Low CA (<)			.		.		.		.

In [11]:

```python
# Figure 7: High vs Low CA Comparison Bar Chart
fig, ax = plt.subplots(figsize=(10, 6))

outcome_labels = ['Growth (GO1)', 'Satisfaction (NPS1)', 'Self-Efficacy (
high_ca_means = [
    df[df['CA1_binary'] == 'High CA']['GO1'].mean(),
    df[df['CA1_binary'] == 'High CA']['NPS1'].mean(),
    df[df['CA1_binary'] == 'High CA']['SE1'].mean(),
    df[df['CA1_binary'] == 'High CA']['RLS1'].mean() / 2  # Scale to 1-5
]
low_ca_means = [
    df[df['CA1_binary'] == 'Low CA']['GO1'].mean(),
    df[df['CA1_binary'] == 'Low CA']['NPS1'].mean(),
    df[df['CA1_binary'] == 'Low CA']['SE1'].mean(),
    df[df['CA1_binary'] == 'Low CA']['RLS1'].mean() / 2  # Scale to 1-5
]

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

bars1 = ax.bar(x - width/2, high_ca_means, width, label=f'High CA (≥{ca_m
bars2 = ax.bar(x + width/2, low_ca_means, width, label=f'Low CA (<{ca_med

ax.set_ylabel('Mean Score')
ax.set_title('Outcome Comparison: High vs Low Conflict Adaptation Teams')
ax.set_xticks(x)
ax.set_xticklabels(outcome_labels)
ax.legend()
ax.set_ylim(0, 5.5)

# Add value labels
for bar in bars1:
    ax.annotate(f'{bar.get_height():.2f}', xy=(bar.get_x() + bar.get_widt
                ha='center', va='bottom', fontsize=9)
for bar in bars2:
    ax.annotate(f'{bar.get_height():.2f}', xy=(bar.get_x() + bar.get_widt
                ha='center', va='bottom', fontsize=9)

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



. Conflict Adaptation by Section

In [12]:

```
# Table: CA1 and outcomes by section
section_stats = df.groupby('Section').agg({
    'CA1': ['mean', 'std', 'count'],
    'GO1': 'mean',
    'NPS1': 'mean',
    'RLS1': 'mean'
}).round(2)
section_stats.columns = ['CA1 Mean', 'CA1 Std', 'N', 'GO1 Mean', 'NPS1 Me
section_stats
```

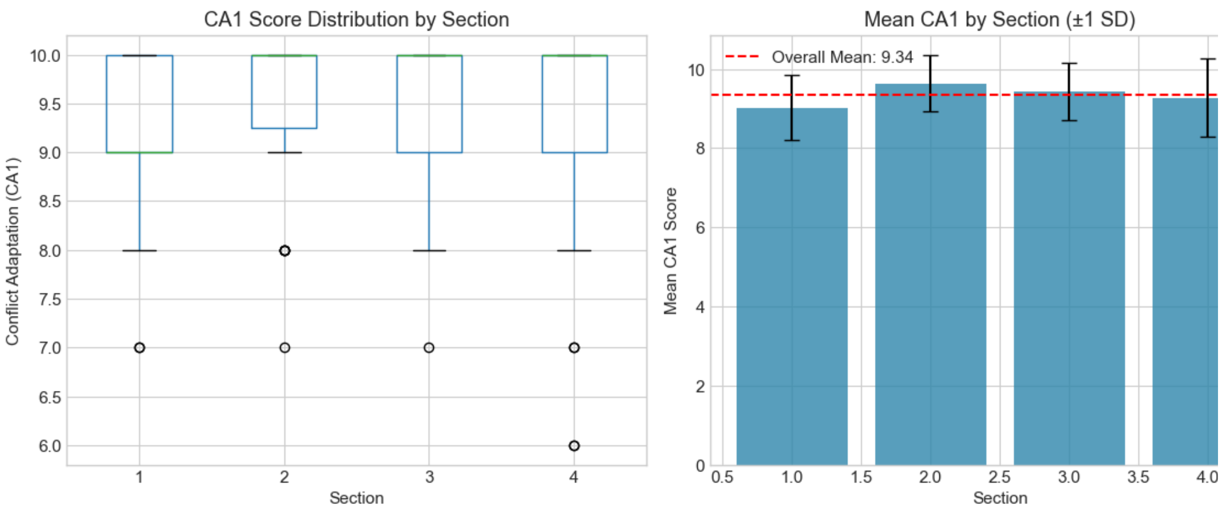
Out[12]:

Section	CA Mean	CA Std	N	GO Mean	NPS Mean	RLS Mean
	.	.		.	.	.
	.	.		.	.	.
	.	.		.	.	.
	.	.		.	.	.

In [13]:

```
# Figure 8: CA1 Distribution by Section
fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# Box plot
df.boxplot(column='CA1', by='Section', ax=axes[0])
axes[0].set_xlabel('Section')
axes[0].set_ylabel('Conflict Adaptation (CA1)')
axes[0].set_title('CA1 Score Distribution by Section')
plt.suptitle('')
```

```
# Bar chart of means with error bars
section_means = df.groupby('Section')['CA1'].mean()
section_stds = df.groupby('Section')['CA1'].std()
sections = section_means.index

axes[1].bar(sections, section_means, yerr=section_stds, capsize=5, color=
axes[1].set_xlabel('Section')
axes[1].set_ylabel('Mean CA1 Score')
axes[1].set_title('Mean CA1 by Section (±1 SD)')
axes[1].axhline(y=df['CA1'].mean(), color='red', linestyle='--', label=f'
axes[1].legend()

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



Summary of Key Findings

Key observations from Conflict Adaptation (CA) analysis:

. **Distribution**: Most teams report moderate-to-high conflict adaptation scores (median aroun
  - /   )

. **Correlations**: CA   shows positive correlations with all outcome variables - teams that ha
conflict well tend to report better outcomes

. **Strongest relationships**:

- CA   correlates most strongly with RLS   (relationship strength) and NPS   (tean
satisfaction)
- Constructive conflict handling appears linked to stronger interpersonal bonds

. **High vs Low CA**: Teams with above-median CA   scores show consistently higher mean
all outcome metrics

. **Section differences**: Some variation exists between sections in conflict adaptation patterns