

```
In [1]: import sys
        from pathlib import Path

        # Add project root to Python path
        ROOT = Path.cwd().parent # adjusts if notebook is in /notebooks/
        sys.path.append(str(ROOT))
```

```
In [2]: import pandas as pd
        import seaborn as sns
        import matplotlib.pyplot as plt

        from pathlib import Path
        from src.stats import group_descriptives, independent_t

        ROOT = Path.cwd().parents[0] # adjust if needed
        data_path = ROOT / "data" / "processed" / "study_results_clean.csv"

        df = pd.read_csv(data_path)
        df.head()
```

Out[2]:

	participant	group	correct_1	correct_2	correct_3	correct_4	correct_5	correct_6	correct_7	correct_8	...	abs_19	cws_19	p_20	abs_20	cws_20
0	CG1	CG	0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	...	1.000000	0.400000	1.000000	0.000000	0.000000
1	CG2	CG	0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	...	0.500000	0.600000	0.000000	1.000000	0.400000
2	CG3	CG	0	1.0	0.0	1.0	1.0	0.0	1.0	0.0	...	1.500000	1.000000	1.000000	0.000000	0.000000
3	CG4	CG	1	1.0	0.0	1.0	1.0	1.0	1.0	1.0	...	1.500000	1.000000	0.833333	0.305556	0.066667
4	CG5	CG	1	1.0	0.0	0.0	0.0	1.0	1.0	1.0	...	0.555556	0.133333	0.500000	0.750000	0.200000

5 rows x 107 columns

```
In [3]: # ----- Significance level / CI settings -----
        ALPHA = 0.05 # 0.05 for 95% CI, 0.10 for 90% CI, etc.
        CI_LEVEL = 100 * (1 - ALPHA)

        print(f"Using alpha = {ALPHA:.2f}, so CI level = {CI_LEVEL:.0f}%")

        Using alpha = 0.05, so CI level = 95%
```

```
In [4]: AVAILABLE_SCORES = {
        "accuracy": "accuracy",
        "abs": "total_abs",
        "cws": "total_cws",
        }

        for label, dv_col in AVAILABLE_SCORES.items():
            print(f"\n=== {label.upper()} ({dv_col}) ===")
            display(group_descriptives(df, dv_col))
            print(independent_t(df, dv_col))

        === ACCURACY (accuracy) ===
        group  n      mean      sd      se
0  CG  21  0.554762  0.147398  0.032165
1  EG  21  0.492857  0.135357  0.029537

        {'dv': 'accuracy', 'group1': 'CG', 'group2': 'EG', 'mean1': np.float64(0.5547619047619048), 'mean2': np.float64(0.4928571428571428), 't': np.float64(1.4175727442134127), 'p': np.float64(0.16411428526384836), 'cohens_d': np.float64(0.4374724464941704), 'n1': 21, 'n2': 21}

        === ABS (total_abs) ===
        group  n      mean      sd      se
0  CG  21  21.531746  2.119106  0.462427
1  EG  21  20.882275  2.188563  0.477584

        {'dv': 'total_abs', 'group1': 'CG', 'group2': 'EG', 'mean1': np.float64(21.53174603174603), 'mean2': np.float64(20.882275132275133), 't': np.float64(0.9769798880762011), 'p': np.float64(0.33445712468125477), 'cohens_d': np.float64(0.3015025391514949), 'n1': 21, 'n2': 21}

        === CWS (total_cws) ===
        group  n      mean      sd      se
0  CG  21  12.288889  1.876798  0.409551
1  EG  21  11.326984  1.885843  0.411525

        {'dv': 'total_cws', 'group1': 'CG', 'group2': 'EG', 'mean1': np.float64(12.288888888888891), 'mean2': np.float64(11.326984126984128), 't': np.float64(1.6567719951747502), 'p': np.float64(0.10539040883048943), 'cohens_d': np.float64(0.5112909379576854), 'n1': 21, 'n2': 21}
```

```
In [5]: for label, dv_col in AVAILABLE_SCORES.items():
        print(f"\n=== {label.upper()} ({dv_col}) ===")
        display(group_descriptives(df, dv_col))
        print(independent_t(df, dv_col))

        === ACCURACY (accuracy) ===
        group  n      mean      sd      se
0  CG  21  0.554762  0.147398  0.032165
1  EG  21  0.492857  0.135357  0.029537

        {'dv': 'accuracy', 'group1': 'CG', 'group2': 'EG', 'mean1': np.float64(0.5547619047619048), 'mean2': np.float64(0.4928571428571428), 't': np.float64(1.4175727442134127), 'p': np.float64(0.16411428526384836), 'cohens_d': np.float64(0.4374724464941704), 'n1': 21, 'n2': 21}

        === ABS (total_abs) ===
        group  n      mean      sd      se
0  CG  21  21.531746  2.119106  0.462427
1  EG  21  20.882275  2.188563  0.477584

        {'dv': 'total_abs', 'group1': 'CG', 'group2': 'EG', 'mean1': np.float64(21.53174603174603), 'mean2': np.float64(20.882275132275133), 't': np.float64(0.9769798880762011), 'p': np.float64(0.33445712468125477), 'cohens_d': np.float64(0.3015025391514949), 'n1': 21, 'n2': 21}

        === CWS (total_cws) ===
        group  n      mean      sd      se
0  CG  21  12.288889  1.876798  0.409551
1  EG  21  11.326984  1.885843  0.411525

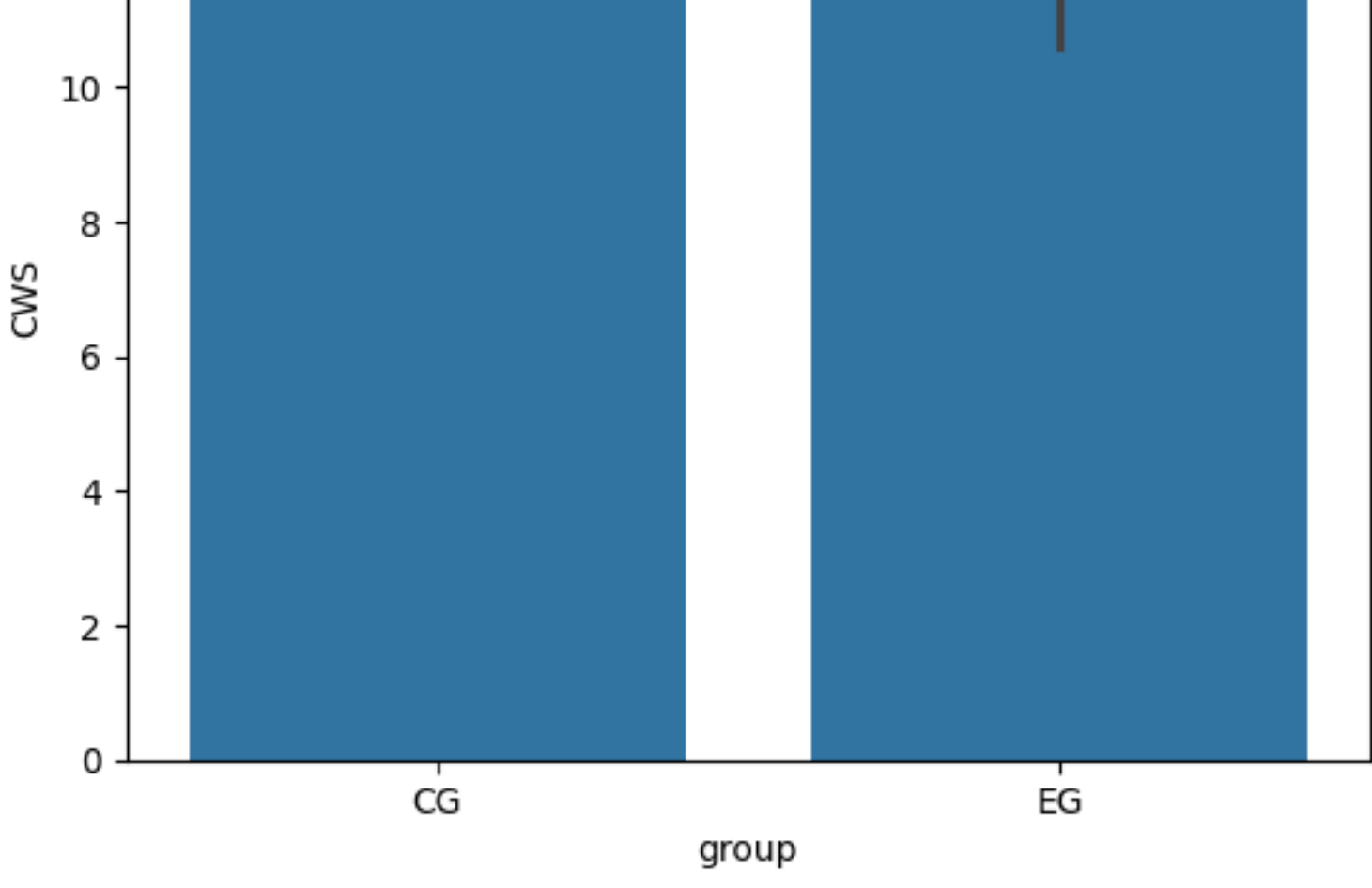
        {'dv': 'total_cws', 'group1': 'CG', 'group2': 'EG', 'mean1': np.float64(12.288888888888891), 'mean2': np.float64(11.326984126984128), 't': np.float64(1.6567719951747502), 'p': np.float64(0.10539040883048943), 'cohens_d': np.float64(0.5112909379576854), 'n1': 21, 'n2': 21}
```

```
In [6]: SCORING_METHOD = "cws" # or "accuracy", "abs", "cws"
        DV = AVAILABLE_SCORES[SCORING_METHOD]

        print(group_descriptives(df, DV))
        print(independent_t(df, DV))

        sns.barplot(data=df, x="group", y=DV, errorbar=('ci', CI_LEVEL))
        plt.title(f"{SCORING_METHOD.upper()} by group")
        plt.ylabel(SCORING_METHOD.upper())
        plt.show()

        group  n      mean      sd      se
0  CG  21  12.288889  1.876798  0.409551
1  EG  21  11.326984  1.885843  0.411525
        {'dv': 'total_cws', 'group1': 'CG', 'group2': 'EG', 'mean1': np.float64(12.288888888888891), 'mean2': np.float64(11.326984126984128), 't': np.float64(1.6567719951747502), 'p': np.float64(0.10539040883048943), 'cohens_d': np.float64(0.5112909379576854), 'n1': 21, 'n2': 21}
```



```
In [7]: results = []

        for label, dv_col in AVAILABLE_SCORES.items():
            res = independent_t(df, dv_col) # this returns two-tailed p
            res["label"] = label

            # --- convert to one-tailed for H1: CG > EG ---
            p_two = res["p"]
            mean1 = res["mean1"] # CG mean (group 1)
            mean2 = res["mean2"] # EG mean (group 2)

            if mean1 > mean2:
                # effect is in hypothesised direction (CG > EG)
                p_one = p_two / 2
                direction = "CG > EG (hypothesised)"
            else:
                # opposite direction
                p_one = 1 - p_two / 2
                direction = "CG ≤ EG (opposite)"

            res["p_one_tailed"] = p_one
            res["sig_alpha_{ALPHA}"] = p_one < ALPHA
            res["direction"] = direction

            results.append(res)

        results_df = pd.DataFrame(results)[
            ["label", "dv", "mean1", "mean2", "t", "p", "p_one_tailed",
             f"sig_alpha_{ALPHA}", "cohens_d", "n1", "n2", "direction"]
        ]

        results_df
```

Out[7]:

	label	dv	mean1	mean2	t	p	p_one_tailed	sig_alpha_0.05	cohens_d	n1	n2	direction
0	accuracy	accuracy	0.554762	0.492857	1.417573	0.164114	0.082057	False	0.437472	21	21	CG > EG (hypothesised)
1	abs	total_abs	21.531746	20.882275	0.976980	0.334457	0.167229	False	0.301503	21	21	CG > EG (hypothesised)
2	cws	total_cws	12.288889	11.326984	1.656772	0.105390	0.052695	False	0.511291	21	21	CG > EG (hypothesised)

```
In [8]: import os

        # Create figures directory if it doesn't exist
        os.makedirs("./figures", exist_ok=True)

        for label, dv_col in AVAILABLE_SCORES.items():
            plt.figure()
            sns.barplot(data=df, x="group", y=dv_col, errorbar=('ci', CI_LEVEL))
            plt.title(f"{label.upper()} by group")
            plt.ylabel(label.upper())
            plt.savefig(f"./figures/{label}_by_group.png", dpi=300, bbox_inches="tight")
            plt.show()
```

