Handheld VESAD Analysis

June 21, 2018

The analysis of the experiment data is also accessible online: https://github.com/NormandErwan/HandheldVesadAnalysis/blob/master/Handheld%20VESAD%20Analysis.ipynb.

0.1 1. Data preparation

Configuration :

```
In [1]: # Imports
        import numpy as np
        import pandas as pd
        from pandas.api.types import CategoricalDtype
        import itertools

        import seaborn as sns
        import matplotlib as mpl
        import matplotlib.pyplot as plt
        import matplotlib.ticker as ticker
        import matplotlib.patches as patches

        from scipy import stats
        import statsmodels.api as sm
        from statsmodels.formula.api import ols
        from statsmodels.stats.multicomp import (MultiComparison, pairwise_tukeyhsd)
        from statsmodels.stats.multitest import multipletests
        from statsmodels.stats.libqsturng import psturng

        from ast import literal_eval
        from os import listdir
        from os.path import join

        from IPython.html.services.config import ConfigManager
```

```
In [2]: # Notebook configuration
        %matplotlib inline

        # Ruler
        ip = get_ipython()
        cm = ConfigManager(parent=ip)
        cm.update('notebook', {"ruler_column": [80]})
```

```
# Style and size of the figures
subplotsize = (5, 4)
legend_fontsize = sns.plotting_context('notebook')['axes.labelsize']
legend_title_fontsize = legend_fontsize + 1
sns.set(context='notebook', style='whitegrid', font_scale=1.25,
        rc={'legend.fontsize': legend_fontsize, 'savefig.dpi': 300,
            'savefig.bbox': 'tight'})

# Render the plots with this language
#language = 'English'
language = 'Français'
```

Data are loaded in the following variables: - Participants information, from the questionary before the trials: `participants` - The summary of the trials of the participants: `raw_trials` - Trials averaged so that each participants ends up with a single observation (there was two trials per condition per participant) (Tip 9 of Dragicevic (2016)) : `trials` - The detailed measures of the trials: `trial_details` - The ranks of the participants from the post-questionary: `ranks`

```
In [3]: participants = pd.read_csv('participants.csv')
        raw_trials = pd.read_csv('participant_trials.csv')
        trials_for_anova = pd.read_csv('participant_trials.csv')
        ranks = pd.read_csv('participant_ranks.csv')
```

```
In [4]: # Detailled trials are long to load, keep commented if unused

        #trial_details = []
        #for file in listdir('.'):
        #    if file.endswith('details.csv'): # The trial files end with *-details.csv
        #        details.append(pd.read_csv(file))
        #trial_details = pd.concat(details, ignore_index=True)
```

Creates independent variables lists (`participants_ivs`, `trials_ivs`) and dependent variables lists (`ranks_dvs`, `trials_dvs`) to make easier to use algorithms and to plot figures.

```
In [5]: # Participants IVs
        if language == 'Français':
            participants_iv_labels = ['Numéro participant', 'Sexe',
                                      'Porte des lunettes', 'Porte des lentilles',
                                      'Est daltonien', 'Intervalle d\'âge',
                                      'Main dominante', 'Main utilisée pour la souris',
                                      'Activité principale',
                                      'Utilisation de l\'ordinateur (heures/jours)',
                                      'Logiciels 3D utilisés',
                                      'Visiocasques RV/RA utilisés',
                                      'Techniques d\'interactions RV/RA utilisées']
        else:
            participants_iv_labels = ['Participant Id', 'Sex', 'Has Glasses',
                                      'Has Contact Lenses', 'Is Color Blind',
                                      'Age Class', 'Dominant Hand',
                                      'Hand Used for Mouse', 'Activity',
                                      'Computer Hours per Day', '3D Softwares Used',
```

```
                                'HMD Used',
                                'Known Interactions Techniques on HMD']

participants_ivs = pd.Series(data=participants_iv_labels,
                             index=participants.columns)
```

In [6]:
```
# Trials IVs
if language == 'Français':
    trials_iv_labels = ['Technique', 'Taille du texte', 'Distance', 'Groupe',
                        'Méthode d\'entrée', 'Méthode d\'affichage']
else:
    trials_iv_labels = ['Technique', 'Text Size', 'Distance', 'Ordering',
                        'Technique Input', 'Technique Output']

trials_ivs = ['technique', 'text_size',
              'distance', 'ordering', 'input', 'output']
trials_ivs = pd.DataFrame(columns=trials_ivs,\
                          index=['label', 'categorical', 'palette'])

default_palette = sns.color_palette('Set2', 8)

for iv_index, iv_label in zip(trials_ivs.columns, trials_iv_labels):
    iv_categories = raw_trials.sort_values([iv_index + '_id'])\
    .drop_duplicates(iv_index)[iv_index]
    iv_categorical = pd.Categorical(iv_categories, iv_categories, ordered=True)
    trials_ivs[iv_index] = [iv_label, iv_categorical, default_palette]

technique_palette = [default_palette[1], default_palette[0], default_palette[2]]
trials_ivs.at['palette', 'technique'] = technique_palette
trials_ivs.at['palette', 'text_size'] = sns.light_palette(
    default_palette[6], 3)[1:3]  # Brown paired colors
trials_ivs.at['palette', 'distance'] = sns.light_palette(
    default_palette[4], 3)[1:3]  # Green paired colors
trials_ivs.at['palette', 'ordering'] = technique_palette
trials_ivs.at['palette', 'input'] = [default_palette[5], default_palette[2]]
trials_ivs.at['palette', 'output'] = [default_palette[0],
                                      sns.color_palette('muted')[5]]
```

In [7]:
```
# Trials DVs
if language == 'Français':
    trials_dv_labels = ['Temps de complétion (s)', 'Sélections',
                        'Temps en sélection', 'Distance 3D en sélection',
                        'Distance en sélection', 'Déselections', 'Erreurs',
                        'Disques classés', 'Défilements', 'Temps de défilement',
                        'Distance 3D de défilement', 'Distance de défilement',
                        'Zooms', 'Temps de zoom', 'Distance 3D de zoom',
                        'Distance de zoom', 'Mouvements tête-téléphone',
                        'Distance relative tête-téléphone']
else:
    trials_dv_labels = ['Task Completion Time (s)', 'Selections',
                        'Selection Time', 'Selection Distance',
```

```
                             'Selection Distance on Grid', 'Deselections', 'Errors',
                             'Items Classified', 'Pans', 'Pan Time', 'Pan Distance',
                             'Pan Distance on Grid', 'Zooms', 'Zoom Time',
                             'Zoom Distance', 'Zoom Distance on Grid',
                             'Phone-Head Motion', 'Signed Phone-Head Motion']

trials_dvs = raw_trials.loc[:, 'total_time':'signed_head_phone_distance'].columns
trials_dvs = pd.Series(data=trials_dv_labels, index=trials_dvs)
```

```
In [8]: # Ranks DVs
        if language == 'Français':
            ranks_dv_labels = ['Facile à comprendre', 'Mentalement facile à utiliser',
                               'Physiquement facile à utiliser', 'Rapidité', 'Réussite',
                               'Frustration', 'Préférence']
        else:
            ranks_dv_labels = ['Easy to Understand', 'Mentally Easy to Use',
                               'Physically Easy to Use', 'Subjective Speed',
                               'Subjective Performance', 'Frustration', 'Preference']

        ranks_dv_scales = [pd.Categorical(list(range(1, 6)), list(
            range(1, 6)), ordered=True)] * len(ranks_dv_labels)

        RdYlBu = sns.color_palette('RdYlBu', 5)
        ranks_dv_palettes = [sns.color_palette('RdYlBu', 5)] * len(ranks_dv_labels)

        ranks_dvs = ranks.loc[:, 'easy_understand':'preference'].columns
        ranks_dvs = pd.DataFrame(data=[ranks_dv_labels, ranks_dv_scales,
                                       ranks_dv_palettes],
                                 columns=ranks_dvs, index=['label', 'scale', 'palette'])

        ranks_dvs.at['scale', 'preference'] = pd.Categorical(
            list(range(1, 4)), list(range(1, 4)), ordered=True)
        ranks_dvs.at['palette', 'preference'] = [RdYlBu[4], RdYlBu[2], RdYlBu[0]]
```

```
In [9]: # Shortcuts
        participant_id = participants_ivs['participant_id']
        technique = trials_ivs['technique']
        text_size = trials_ivs['text_size']
        distance = trials_ivs['distance']
        ordering = trials_ivs['ordering']
        iv_input = trials_ivs['input']
        iv_output = trials_ivs['output']

        total_time = trials_dvs['total_time']
```

Clean the data:

```
In [10]: # Set better and translated columns to participants, trials and ranks
         participants.columns = participants_ivs

         columns = []
```

```
for column in raw_trials.columns:
    if (column in participants_ivs.index):
        columns.append(participants_ivs[column])
    elif (column in trials_ivs.columns):
        columns.append(trials_ivs[column]['label'])
    elif (column in trials_dvs.index):
        columns.append(trials_dvs[column])
    else:
        columns.append(column)

raw_trials.columns = columns

ranks.columns = [participant_id, ordering['label'],
                 technique['label']] + ranks_dvs.loc['label', :].tolist()
```

In [11]:
```
# Set the participant_id column as the index in participants
participants.set_index(participants_ivs['participant_id'], inplace=True)
```

In [12]:
```
# Some participants are non valid or don't have complete measures
non_valid_participants = [0, 4]
participants = participants[~participants.index.isin(non_valid_participants)]
ranks = ranks[~ranks[participants_ivs['participant_id']]
              .isin(non_valid_participants)]

incomplete_trials_participant_ids = [0, 4]
raw_trials = raw_trials[~raw_trials[participants_ivs['participant_id']]
                        .isin(incomplete_trials_participant_ids)
                       ].reset_index(drop=True)
trials_for_anova = trials_for_anova[~trials_for_anova['participant_id']
                                    .isin(incomplete_trials_participant_ids)
                                   ].reset_index(drop=True)
```

In [13]:
```
# Some participants have wrong head phone mesures
for head_distance_column in ['absolute_head_phone_distance',
                             'signed_head_phone_distance']:
    raw_trials.loc[raw_trials[trials_dvs[head_distance_column]] == 0,
                   trials_dvs['absolute_head_phone_distance']] = np.nan
    trials_for_anova.loc[trials_for_anova[head_distance_column] == 0,
                         head_distance_column] = np.nan
```

In [14]:
```
# Setup categorical columns participants, trials and ranks
participants[ordering['label']] = ranks.groupby(
    participant_id)[ordering['label']].first()
participants[ordering['label']] = participants[ordering['label']].astype(
    ordering['categorical'])

for iv_index in trials_ivs.columns:
    iv = trials_ivs[iv_index]
    raw_trials[iv['label']] = raw_trials[iv['label']].astype(iv['categorical'])
    trials_for_anova[iv_index] = raw_trials[iv['label']]
```

```
    ranks[technique['label']] = ranks[technique['label']].astype(
        technique['categorical'])
    ranks[ordering['label']] = ranks[ordering['label']].astype(
        ordering['categorical'])

    # Rename categories
    if language == 'Français':
        technique['categorical'].categories = ['Téléphone', 'VESAD tactile', 'VESAD']
        text_size['categorical'].categories = ['Grand', 'Petit']
        distance['categorical'].categories = ['Proche', 'Loin']
        ordering['categorical'].categories = ['Groupe 1', 'Groupe 2', 'Groupe 3']
        iv_input['categorical'].categories = ['Tactile', 'Autour du téléphone']
        iv_output['categorical'].categories = ['Téléphone seul', 'Téléphone étendu']
    else:
        ordering['categorical'].categories = ['Group 1', 'Group 2', 'Group 3']

    # Set renamed categories to data
    participants[trials_ivs['ordering']['label']
                 ].cat.categories = ordering['categorical'].categories

    for iv_index in trials_ivs.columns:
        iv = trials_ivs[iv_index]
        raw_trials[iv['label']].cat.categories = iv['categorical'].categories

    ranks[technique['label']].cat.categories = technique['categorical'].categories
    ranks[ordering['label']].cat.categories = ordering['categorical'].categories
```

In [15]:
```
# Eval the arrays in some dvs
def eval_if_str(data):
    return literal_eval(data) if isinstance(data, str) else data

raw_trials['grid_config'] = raw_trials['grid_config'].apply(eval_if_str)
```

In [16]:
```
# Create trials
trials_groupby_ivs = [participants_ivs['participant_id']]\
                     + trials_ivs.loc['label', :].tolist()
trials = raw_trials.groupby(trials_groupby_ivs, observed=True)\
         .mean().reset_index()
```

Utilities:

In [17]:
```
# Figure labels in the selected language
labels = pd.Series()

if language == 'Français':
    labels['category'] = 'Catégorie'
    labels['count'] = 'Nombre total'
    labels['distance'] = 'Distance moyenne (m)'
    labels['dv'] = 'VD'
    labels['iv'] = 'VI'
    labels['iv_value'] = 'Valeur VI'
```

```
        labels['mean_difference'] = 'Différence des moyennes'
        labels['mean_difference_percentage'] = 'Différence des moyennes (%)'
        labels['mean_rank'] = 'Note moyenne'
        labels['preferences'] = ['Premier', 'Deuxième', 'Troisième']
        labels['p_value'] = 'Valeur p'
        labels['question'] = 'Question'
        labels['rank'] = 'Note'
        labels['time'] = 'Temps moyen (s)'
        labels['t_statistic'] = 'Statistique T'
        labels['votes'] = 'Participants'
    else:
        labels['category'] = 'Category'
        labels['count'] = 'Count'
        labels['distance'] = 'Mean Distance (m)'
        labels['dv'] = 'DV'
        labels['iv'] = 'IV'
        labels['iv_value'] = 'IV Value'
        labels['mean_difference'] = 'Mean Difference'
        labels['mean_difference_percentage'] = 'Mean Difference Percentage'
        labels['mean_rank'] = 'Mean Rank'
        labels['preferences'] = ['First', 'Second', 'Third']
        labels['p_value'] = 'p-value'
        labels['question'] = 'Question'
        labels['rank'] = 'Rank'
        labels['time'] = 'Mean Time (s)'
        labels['t_statistic'] = 'T statistic'
        labels['votes'] = 'Participants'
```

In [18]:
```
def mean_ci(x, which=95, n_boot=1000):
    """Returns the confidence interval of the mean"""
    x2 = [i for i in x if not np.isnan(i)]
    boots = sns.algorithms.bootstrap(x2, n_boot=n_boot)
    return sns.utils.ci(boots, which=which)
```

In [19]:
```
def print_mean_ci(x, ci_which=95):
    """Returns a string containing the mean with the CI of x"""
    ci1, ci2 = mean_ci(x, which=ci_which)
    return '{:.2f} [{:.2f}, {:.2f}]'.format(np.mean(x), ci1, ci2)
```

In [20]:
```
def exp_mean(x):
    return np.exp(np.mean(x))
```

In [21]:
```
def print_exp_mean_ci(x, ci_which=95):
    ci1, ci2 = np.exp(mean_ci(x, which=ci_which))
    return '{:.2f} [{:.2f}, {:.2f}]'.format(np.exp(np.mean(x)), ci1, ci2)
```

In [22]:
```
def mean_difference(a, b):
    """Returns the mean difference value and percentage between a and b"""
    mean_diff = np.mean(a) - np.mean(b)
    mean_diff_percentage = mean_diff / np.mean(b) * 100
    return (mean_diff, mean_diff_percentage)
```

```
In [23]: def p_values_correction(data, alpha=0.05, correction_method='fdr_bh'):
             if correction_method != None:
                 reject, p_values_corrected, a1, a2 =\
                     multipletests(data[labels['p_value']].tolist(), alpha=alpha,
                                   method=correction_method)
                 data[labels['p_value']] = p_values_corrected
```

```
In [24]: def subplots(nsubplots, ncols_max=2, subplotsize=subplotsize, *plt_args):
             ncols = min(ncols_max, nsubplots)
             nrows = ((nsubplots - 1) // ncols) + 1
             fig, axs = plt.subplots(nrows=nrows, ncols=ncols,\
                                     figsize=(subplotsize[0]*ncols, subplotsize[1]*nrows),
                                     *plt_args)

             if nrows == 1 and ncols == 1:
                 axs = [axs]
             elif nrows >= 2 and ncols >= 2:
                 axs = [ax for ax_row in axs for ax in ax_row]

             for ax in axs[::-1][0:len(axs) - nsubplots]:
                 fig.delaxes(ax)

             return (fig, axs)
```

```
In [25]: def fix_legend_fontsize(ax_legend, fontsize=legend_title_fontsize):
             plt.setp(ax_legend.get_title(), fontsize=fontsize)
```

```
In [26]: def config_legend(ax, iv_id, fontsize=legend_title_fontsize):
             legend = ax.legend(title=trials_ivs.at['label', iv_id], frameon=True,
                                loc='center left', bbox_to_anchor=(1, 0.5))
             fix_legend_fontsize(legend)
             return legend
```

0.2 2. Participant ranks

Some functions for the analysis:

```
In [27]: def get_ranks_count(iv_index, dv_index):
             iv, dv = trials_ivs[iv_index], ranks_dvs[dv_index]

             ranks_counts_index = pd.MultiIndex.from_product([iv['categorical'],
                                                               dv['scale']],
                                                              names=[iv['label'],
                                                                     labels['rank']])
             # Zero counts by default and gets the counts
             default_counts = pd.Series(0, index=ranks_counts_index)
             ranks_counts = ranks.groupby([iv['label'], dv['label']]).size()

             # Merge and remove duplicated defaults
             ranks_counts = pd.concat([ranks_counts, default_counts])
             ranks_counts = ranks_counts[~ranks_counts.index.duplicated(keep='first')]
```

```
        ranks_counts.sort_index(inplace=True)
        ranks_counts.index = ranks_counts_index # Restore the index
        return ranks_counts
```

```
In [28]: def cumulated_barplot(data, palette, **args):
             for row_id, row in data.iloc[::-1].iterrows():
                 sns.barplot(y=data.columns, x=row, label=row_id,
                             color=palette[row_id-1], orient='h', **args)
```

```
In [29]: def plot_ranks_distributions(iv_id, dv_ids):
             iv = trials_ivs[iv_id]

             fig, axs = subplots(len(dv_ids))
             for dv_id, ax in zip(dv_ids, axs):
                 dv = ranks_dvs[dv_id]

                 cumulated_ranks_count = get_ranks_count(iv_id, dv_id).unstack(level=0)\
                                         .cumsum()
                 cumulated_barplot(cumulated_ranks_count, palette=dv['palette'], ax=ax)
                 ax.set(xlabel=labels['votes'], xlim=(0, cumulated_ranks_count.max()[0]))
                 ax.xaxis.set_major_locator(ticker.MultipleLocator(2)) # Fix the axis ticks

                 ax_handles, ax_labels = ax.get_legend_handles_labels()
                 legend = ax.legend(ax_handles[::-1], ax_labels[::-1], frameon=True,
                                    loc='lower center', bbox_to_anchor=(0.5, 1),
                                    mode=None, ncol=len(dv['scale']), title=dv['label'],
                                    fontsize=legend_fontsize-2)
                 fix_legend_fontsize(legend)

             fig.tight_layout(h_pad=1) # Add padding to avoir legend and labels overlap
             return (fig, axs)
```

```
In [30]: def plot_ranks(iv_id, dv_ids, estimator=np.mean):
             iv = trials_ivs[iv_id]

             fig, axs = subplots(len(dv_ids))
             for dv_id, ax in zip(dv_ids, axs):
                 dv = ranks_dvs[dv_id]

                 sns.barplot(x=iv['label'], y=dv['label'], palette=iv['palette'],
                             data=ranks, ax=ax, estimator=estimator)
                 ax.set(ylim=(0, dv['scale'][-1]))
                 ax.yaxis.set_major_locator(ticker.MultipleLocator(1)) # Fix the axis ticks

             return (fig, axs)
```

```
In [31]: def rank_samples(iv_id, dv_id):
             """Returns the list of ranks (DV) for each IV value"""
             samples = []
             iv = trials_ivs[iv_id]
```

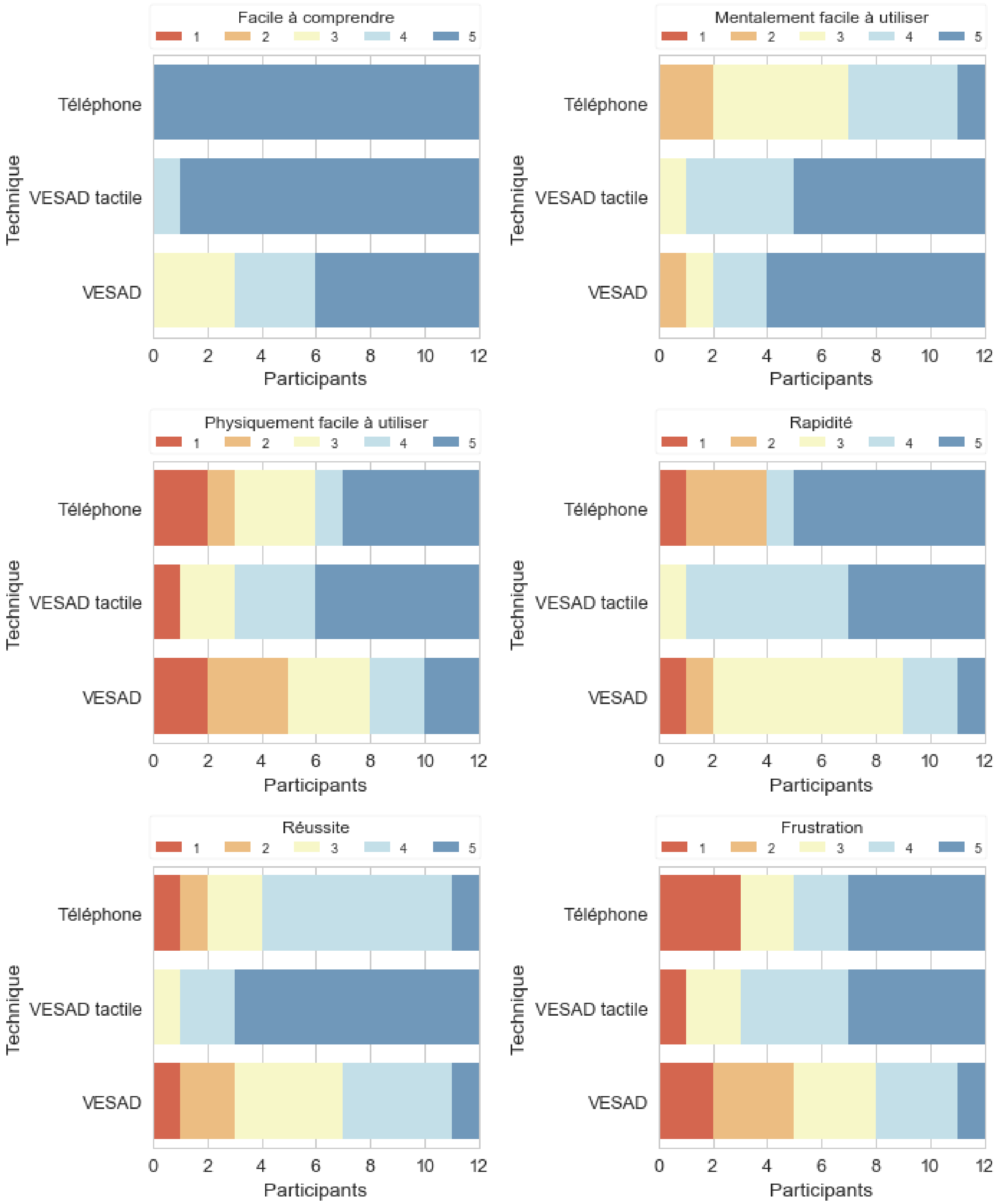
```
        for iv_value in iv['categorical']:
            dv_label = ranks_dvs[dv_id]['label']
            sample = ranks[ranks[iv['label']] == iv_value][dv_label]\
                     .reset_index(drop=True)
            samples.append(sample)
        return samples
```

```
In [32]: def test_ranks(iv_id, dv_ids, **args):
             results = []
             iv = trials_ivs[iv_id]

             for dv_id in dv_ids:
                 dv = ranks_dvs[dv_id]
                 samples = rank_samples(iv_id, dv_id)
                 H, p = stats.kruskal(*samples)
                 results.append([iv['label'], dv['label'], H, p])

             results = pd.DataFrame(results, columns=[labels['iv'], labels['dv'],
                                                      'Kruskal-Wallis H',
                                                      labels['p_value']])
             p_values_correction(results, **args)
             return results
```

```
In [33]: def test_pairwise_ranks(iv_id, dv_ids, **args):
             iv = trials_ivs[iv_id]
             iv_category_ids = range(len(iv['categorical']))

             results = []
             for dv_id in dv_ids:
                 dv = ranks_dvs[dv_id]
                 samples = rank_samples(iv_id, dv_id)
                 sample_pairs = itertools.combinations(iv_category_ids, 2)
                 for id1, id2 in sample_pairs:
                     U, p = stats.mannwhitneyu(samples[id1], samples[id2])
                     mean_diff, mean_diff_per = mean_difference(samples[id1], samples[id2])
                     results.append([iv['label'], iv['categorical'][id1],
                                     iv['categorical'][id2], dv['label'],
                                     mean_diff, mean_diff_per, U, p])

             columns = [labels['iv'], labels['iv_value'] + ' 1',
                        labels['iv_value'] + ' 2', labels['dv'],
                        labels['mean_difference'], labels['mean_difference_percentage'],
                        'Mann-Whitney U', labels['p_value']]
             results = pd.DataFrame(results, columns=columns)
             p_values_correction(results, **args)
             return results
```

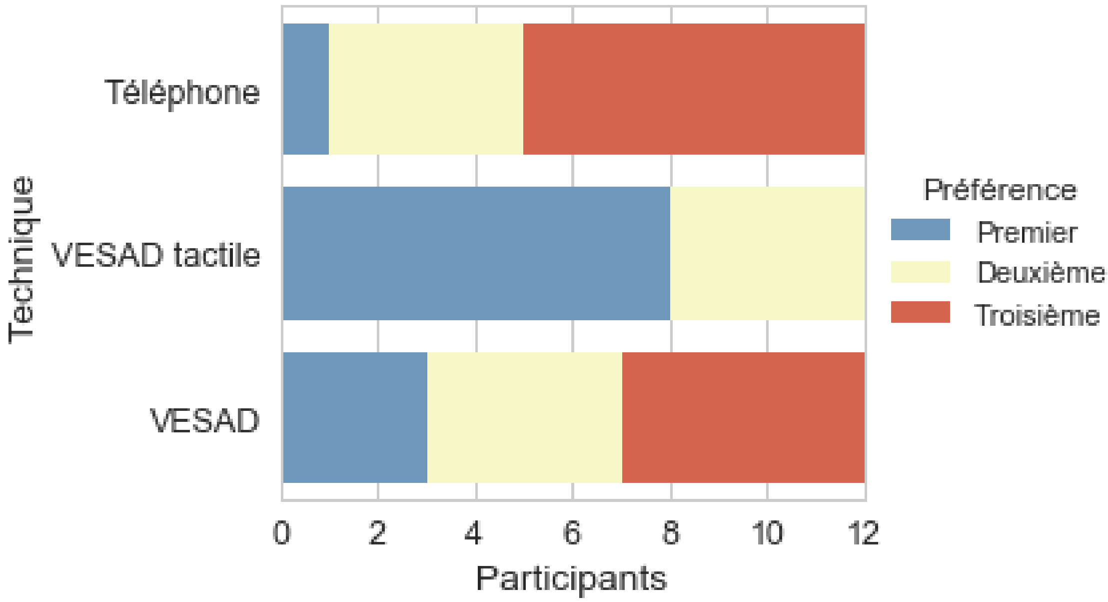
We display the rank and preference distributions:

```
In [34]: (fig, axs) = plot_ranks_distributions('technique', ranks_dvs.columns[0:-1])
         fig.savefig('ranks_distributions.png')
```




```
In [35]: (fig, axs) = plot_ranks_distributions('technique', ['preference'])

         ax_handles, ax_labels = axs[0].get_legend_handles_labels()
         legend = axs[0].legend(ax_handles[::-1], labels['preferences'],
                                loc='center left', bbox_to_anchor=(1, 0.5),
                                title=ranks_dvs['preference']['label'])
```

```
fix_legend_fontsize(legend)

fig.savefig('preferences_distribution.png')
```



We use the Kruskal-Wallis test (Benjamini–Hochberg correction) on each question to check if there is statistical significative differences between the ranks among TECHNIQUE:

```
In [36]: test_ranks('technique', ranks_dvs, correction_method='fdr_bh')
```

Out[36]:

	VI	VD	Kruskal-Wallis H	Valeur p
0	Technique	Facile à comprendre	11.001420	0.007497
1	Technique	Mentalement facile à utiliser	10.905742	0.007497
2	Technique	Physiquement facile à utiliser	4.148121	0.125674
3	Technique	Rapidité	7.130846	0.039599
4	Technique	Réussite	13.784269	0.006303
5	Technique	Frustration	4.500057	0.122962
6	Technique	Préférence	12.638889	0.006303

All the questions, except Physically Easy to Use and Frustration, are statistically significants: Easy to Understand ($p = 0.007$), Mentally Easy to Use ($p = 0.007$), Subjective Speed ($p = 0.04$), Subjective Performance ($p = 0.006$), Preference ($p = 0.006$).

We use then pairwise Mann-Whitney tests (Benjamini–Hochberg correction) for the significant questions above:

```
In [37]: test_pairwise_ranks('technique', ['easy_understand', 'mentally_easy_use',
                                          'could_go_fast', 'subjective_performance',
                                          'preference'], correction_method='fdr_bh')
```

Out[37]:

	VI	Valeur VI 1	Valeur VI 2	VD \
0	Technique	Téléphone	VESAD tactile	Facile à comprendre
1	Technique	Téléphone	VESAD	Facile à comprendre

```
2   Technique  VESAD tactile          VESAD          Facile à comprendre
3   Technique      Téléphone  VESAD tactile  Mentalement facile à utiliser
4   Technique      Téléphone          VESAD  Mentalement facile à utiliser
5   Technique  VESAD tactile          VESAD  Mentalement facile à utiliser
6   Technique      Téléphone  VESAD tactile                       Rapidité
7   Technique      Téléphone          VESAD                       Rapidité
8   Technique  VESAD tactile          VESAD                       Rapidité
9   Technique      Téléphone  VESAD tactile                       Réussite
10  Technique      Téléphone          VESAD                       Réussite
11  Technique  VESAD tactile          VESAD                       Réussite
12  Technique      Téléphone  VESAD tactile                     Préférence
13  Technique      Téléphone          VESAD                     Préférence
14  Technique  VESAD tactile          VESAD                     Préférence

    Différence des moyennes  Différence des moyennes (%)  Mann-Whitney U  \
0                  0.083333                     1.694915            66.0
1                  0.750000                    17.647059            36.0
2                  0.666667                    15.686275            40.5
3                 -1.166667                   -25.925926            23.0
4                 -1.083333                   -24.528302            28.5
5                  0.083333                     1.886792            69.5
6                 -0.500000                   -11.538462            70.5
7                  0.750000                    24.324324            48.5
8                  1.250000                    40.540541            21.0
9                 -1.166667                   -25.000000            22.5
10                 0.333333                    10.526316            57.0
11                 1.500000                    47.368421            17.5
12                 1.166667                    87.500000            16.0
13                 0.333333                    15.384615            56.0
14                -0.833333                   -38.461538            32.0

    Valeur p
0   0.215732
1   0.008605
2   0.020977
3   0.005031
4   0.010151
5   0.475027
6   0.475027
7   0.126838
8   0.004655
9   0.004655
10  0.215732
11  0.003904
12  0.003904
13  0.215732
14  0.013011
```

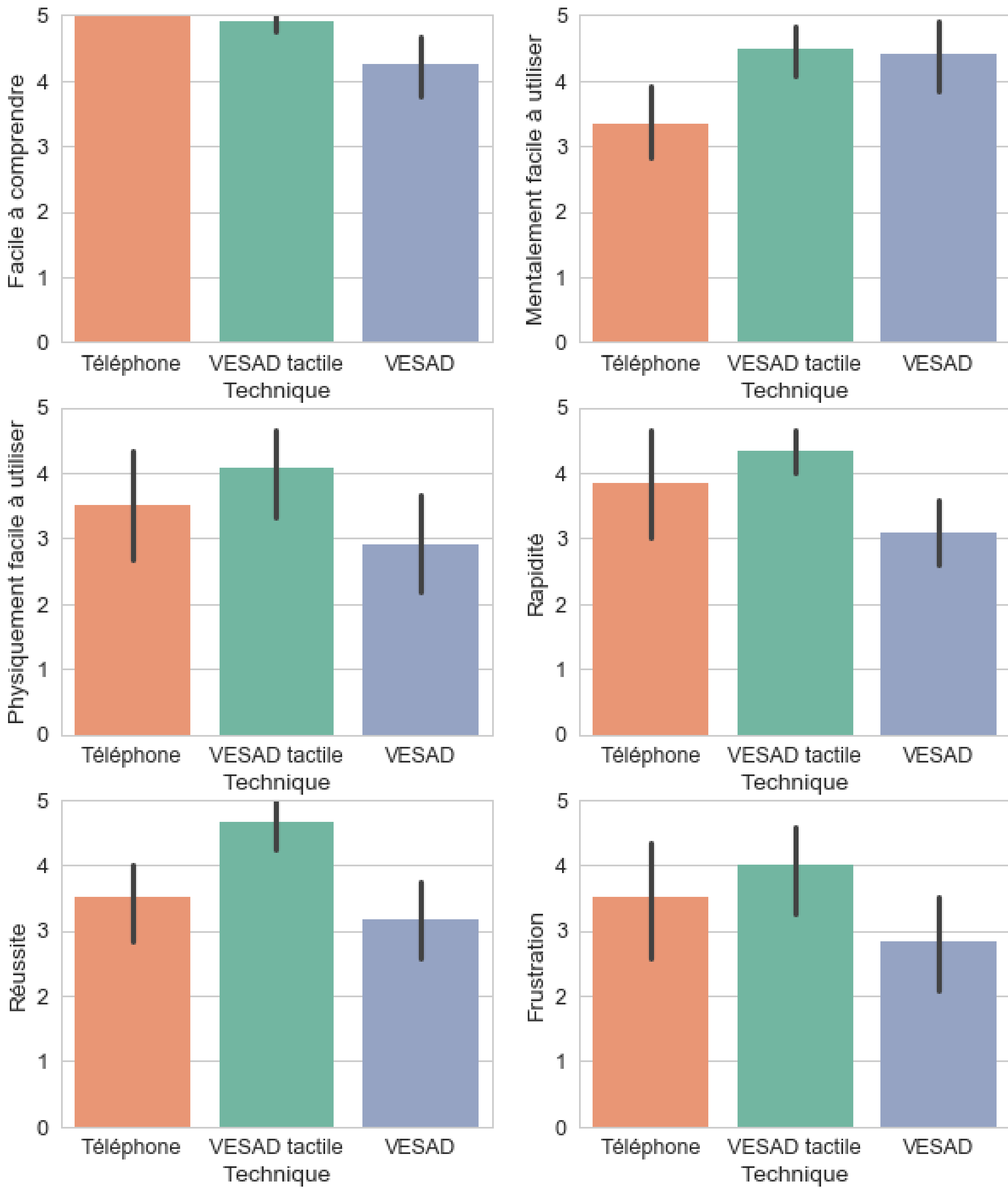
We display the mean and 95% CI of each question:

```
In [38]: ranks.groupby([trials_ivs['technique']['label']])\
```

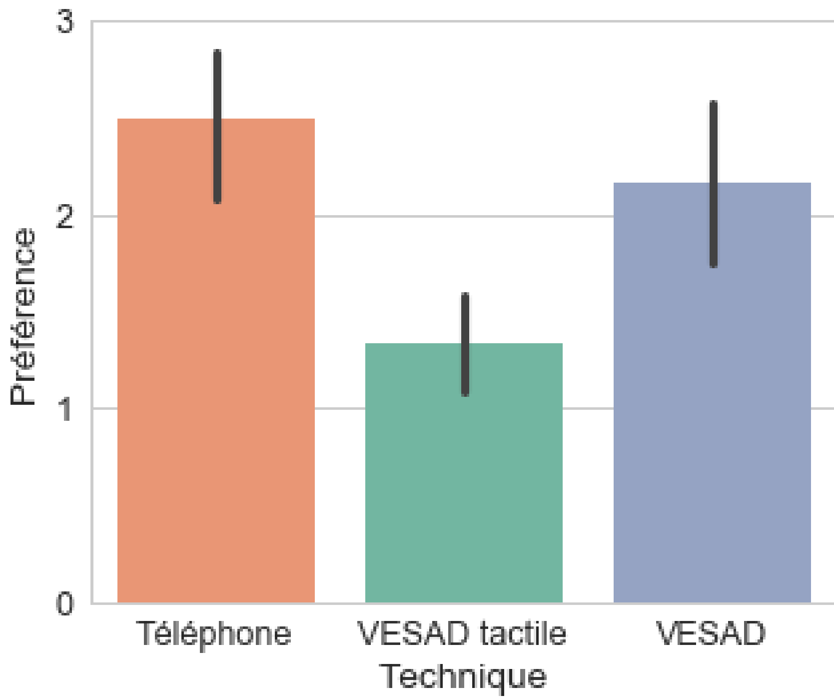
```
        .aggregate(print_mean_ci).loc[:, ranks_dvs.loc['label', :]].transpose()
```

```
Out[38]: Technique                               Téléphone      VESAD tactile  \
         Facile à comprendre              5.00 [5.00, 5.00]  4.92 [4.75, 5.00]
         Mentalement facile à utiliser    3.33 [2.83, 3.83]  4.50 [4.17, 4.83]
         Physiquement facile à utiliser   3.50 [2.58, 4.33]  4.08 [3.33, 4.67]
         Rapidité                         3.83 [2.92, 4.59]  4.33 [4.00, 4.67]
         Réussite                         3.50 [2.83, 4.00]  4.67 [4.25, 5.00]
         Frustration                      3.50 [2.50, 4.33]  4.00 [3.25, 4.58]
         Préférence                       2.50 [2.17, 2.83]  1.33 [1.08, 1.58]

         Technique                                    VESAD
         Facile à comprendre              4.25 [3.75, 4.67]
         Mentalement facile à utiliser    4.42 [3.83, 4.83]
         Physiquement facile à utiliser   2.92 [2.25, 3.67]
         Rapidité                         3.08 [2.50, 3.67]
         Réussite                         3.17 [2.58, 3.75]
         Frustration                      2.83 [2.17, 3.50]
         Préférence                       2.17 [1.75, 2.67]
```

```
In [39]: (fig, axs) = plot_ranks('technique', ranks_dvs.columns[0:-1])
         fig.savefig('ranks.png')
```




```
In [40]: (fig, axs) = plot_ranks('technique', ['preference'])
         fig.savefig('preferences.png')
```



Overall significant results are:

- **Easy to Understand**: *PhoneOnly* is significantly better than *MidAirInArOut* ($p = 0.009$), and seems a little better than *PhoneInArOut*.
- **Physically Easy to Use**: There is no significant differences due to TECHNIQUE; they seem scored similar.
- **Mentally Easy to Use**: *PhoneOnly* is statistically and practically worst than *PhoneInArOut* ($p = 0.005$) and *MidAirInArOut* ($p = 0.01$).
- **Subjective Speed**: *PhoneInArOut* is significantly better than *MidAirInArOut* ($p = 0.05$).
- **Subjective Performance**: *PhoneInArOut* is statistically better than *PhoneOnly* ($p = 0.005$) and *MidAirInArOut* ($p = 0.004$).
- **Frustration**: There is no significant differences due to TECHNIQUE; they seem scored similar.
- **Preference**: *PhoneInArOut* is significantly prefered to *PhoneOnly* ($p = 0.004$) and *MidAirInArOut* ($p = 0.01$).

0.3 3. Participant trials

Some functions for the analysis:

```
In [41]: def trial_samples(iv_id, dv_id, data=trials):
             iv, dv = trials_ivs[iv_id], trials_dvs[dv_id]
             return [data[data[iv['label']] == iv_value][dv]\
                     for iv_value in iv['categorical']]
```

```
In [42]: def trial_means(iv_ids, dv_ids, data=trials, aggregate=print_mean_ci):
             iv_labels = [trials_ivs.at['label', iv_id] for iv_id in iv_ids]
             dv_labels = [trials_dvs[dv_id] for dv_id in dv_ids]
             return data[iv_labels + dv_labels].groupby(iv_labels)\
                                              .aggregate(aggregate)
```

In [43]:
```
def melt_trials(value_vars, var_name, value_name, data=trials):
    return pd.melt(data, id_vars=trials_ivs.loc['label', :],
                   value_vars=value_vars, var_name=var_name,
                   value_name=value_name)
```

In [44]:
```
def test_normality(iv_ids, dv_ids, data=trials, **args):
    results = []

    for dv_id in dv_ids:
        for iv_id in iv_ids:
            iv = trials_ivs[iv_id]
            samples = trial_samples(iv_id, dv_id, data)
            for iv_value, sample in zip(iv['categorical'], samples):
                W, p = stats.shapiro(sample)
                results.append([iv['label'], iv_value, trials_dvs[dv_id], W, p])

    results = pd.DataFrame(results, columns=[labels['iv'], labels['iv_value'],
                                             labels['dv'], 'Shapiro W',
                                             labels['p_value']])
    p_values_correction(results, **args)
    return results
```

In [45]:
```
def test_equal_variances(iv_ids, dv_ids, data=trials, levene_center='mean',
                         **args):
    results = []

    for dv_id in dv_ids:
        for iv_id in iv_ids:
            samples = trial_samples(iv_id, dv_id, data)
            W, p = stats.levene(*samples)
            results.append([trials_ivs.at['label', iv_id], trials_dvs[dv_id],
                            W, p])

    results = pd.DataFrame(results, columns=[labels['iv'], labels['dv'],
                                             'Levene W', labels['p_value']])
    p_values_correction(results, **args)
    return results
```

In [46]:
```
def test_pairwise_trials(iv_id, dv_id, data=trials, log_data=False, **args):
    results = []
    iv, dv = trials_ivs[iv_id], trials_dvs[dv_id]
    iv_category_ids = range(len(iv['categorical']))

    samples = trial_samples(iv_id, dv_id, data)
    sample_pairs = itertools.combinations(iv_category_ids, 2)
    for id1, id2 in sample_pairs:
        T, p = stats.ttest_ind(samples[id1], samples[id2])

        mean_diff, mean_diff_per = mean_difference(np.exp(samples[id1]),
                                                   np.exp(samples[id2]))\
            if log_data else mean_difference(samples[id1], samples[id2])
```

```
                results.append([iv['label'], iv['categorical'][id1],
                                iv['categorical'][id2], dv, mean_diff,
                                mean_diff_per, T, p])

        columns = [labels['iv'], labels['iv_value'] + ' 1',
                   labels['iv_value'] + ' 2', labels['dv'],
                   labels['mean_difference'], labels['mean_difference_percentage'],
                   labels['t_statistic'], labels['p_value']]
        results = pd.DataFrame(results, columns=columns)

        p_values_correction(results, **args)
        return results
```

```
In [47]: def test_non_normal_trials(iv_ids, dv_ids, data=trials, **args):
             results = []

             for dv_id in dv_ids:
                 for iv_id in iv_ids:
                     samples = trial_samples(iv_id, dv_id, data)
                     H, p = stats.kruskal(*samples)
                     results.append([trials_ivs.at['label', iv_id], trials_dvs[dv_id],
                                     H, p])

             results = pd.DataFrame(results, columns=[labels['iv'], labels['dv'],
                                                      'Kruskal-Wallis H',
                                                      labels['p_value']])
             p_values_correction(results, **args)
             return results
```

```
In [48]: def test_pairwise_non_normal_trials(iv_ids, dv_ids, data=trials, **args):
             results = []

             for dv_id in dv_ids:
                 for iv_id in iv_ids:
                     iv, dv = trials_ivs[iv_id], trials_dvs[dv_id]
                     samples = trial_samples(iv_id, dv_id, data)

                     iv_category_ids = range(len(iv['categorical']))
                     sample_pairs = itertools.combinations(iv_category_ids, 2)
                     for id1, id2 in sample_pairs:
                         U, p = stats.mannwhitneyu(samples[id1], samples[id2])
                         mean_diff, mean_diff_per = mean_difference(samples[id1],
                                                                    samples[id2])
                         results.append([iv['label'], iv['categorical'][id1],
                                         iv['categorical'][id2], dv, mean_diff,
                                         mean_diff_per, U, p])

             columns = [labels['iv'], labels['iv_value'] + ' 1',
                        labels['iv_value'] + ' 2', labels['dv'],
                        labels['mean_difference'], labels['mean_difference_percentage'],
```

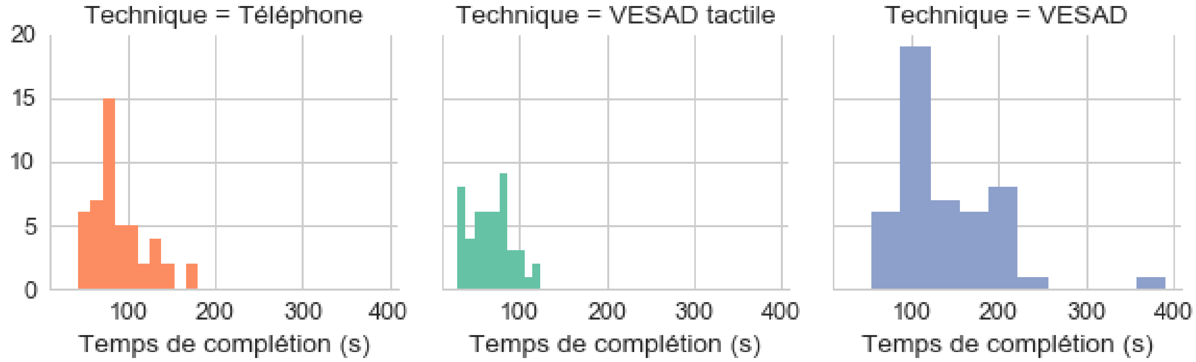
```
                'Mann-Whitney U', labels['p_value']]
    results = pd.DataFrame(results, columns=columns)
    p_values_correction(results, **args)
    return results
```

```
In [49]: def plot_trials(iv_ids_list, dv_id, data=trials, kind='bar', **args):
             dv = trials_dvs[dv_id]
             if (len(iv_ids_list) == 0):
                 iv_ids_list = [[iv_id] for id_id in trials_ivs.columns]

             fig, axs = subplots(len(iv_ids_list))
             for id_ids, ax in zip(iv_ids_list, axs):

                 ivs = [trials_ivs[id_id] for id_id in id_ids]
                 if (len(ivs) == 1):
                     iv = ivs[0]

                     if (kind == 'bar'):
                         sns.barplot(x=iv['label'], y=dv, data=data,
                                     palette=iv['palette'], ax=ax, **args)

                     elif (kind == 'box'):
                         sns.boxplot(x=iv['label'], y=dv, data=data,
                                     palette=iv['palette'], ax=ax, **args)

                     elif (kind == 'count'):
                         sns.countplot(hue=iv['label'], x=dv, data=data,
                                       palette=iv['palette'], ax=ax, **args)
                         ax.set(ylabel='Count')
                         ax.legend(loc='upper right', title=labels['count'],
                                   frameon=True)

                 elif (len(ivs) == 2):
                     if (kind == 'bar'):
                         sns.barplot(x=ivs[1]['label'], y=dv, hue=ivs[0]['label'],
                                     data=data, palette=ivs[0]['palette'], ax=ax, **args)
                     ax.legend(frameon=True, loc='upper left', bbox_to_anchor=(1, 1))

             return (fig, axs)
```

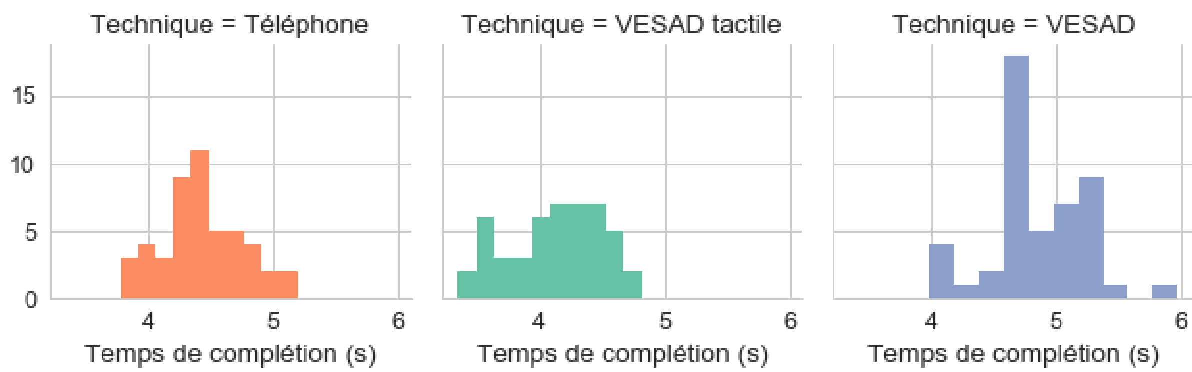
0.3.1 3.1. Task completion time

We first apply a log transform to TCT to approximate a normal distribution.

```
In [50]: g = sns.FacetGrid(trials, col=technique['label'], hue=technique['label'],
                           palette=technique['palette'])
         g.map(plt.hist, total_time)

Out[50]: <seaborn.axisgrid.FacetGrid at 0x125843d1e10>
```




```
In [51]: trials[total_time] = np.log(trials[total_time])
         trials_for_anova['total_time'] = np.log(trials_for_anova['total_time'])

In [52]: g = sns.FacetGrid(trials, col=technique['label'], hue=technique['label'],
                           palette=technique['palette'])
         g.map(plt.hist, total_time)

Out[52]: <seaborn.axisgrid.FacetGrid at 0x125843d1588>
```



We test the normality of TCT distributions for each TECHNIQUE and their equality of variances, since it's the main factor of interest.

```
In [53]: test_normality(['technique'], ['total_time'])
```

Out[53]:

	VI	Valeur VI	VD	Shapiro W	Valeur p
0	Technique	Téléphone	Temps de complétion (s)	0.983679	0.735995
1	Technique	VESAD tactile	Temps de complétion (s)	0.971828	0.446912
2	Technique	VESAD	Temps de complétion (s)	0.966510	0.446912

```
In [54]: test_equal_variances(['technique'], ['total_time'])
```

Out[54]:

	VI	VD	Levene W	Valeur p
0	Technique	Temps de complétion (s)	0.756269	0.471309

We meet all the assumptions of an ANOVA. Trials were done independently, TCT distributions are normal and their variances are equal.

We perform a full factorial ANOVA with the model: TCT ~ TECHNIQUE x TEXT_SIZE x DISTANCE + TECHNIQUE x ORDERING.

```
In [55]: tct_model = ols('total_time ~ technique * text_size * distance'
                         + '+ technique * ordering', data=trials_for_anova).fit()
         sm.stats.anova_lm(tct_model, typ=2)
```

```
Out[55]:                                  sum_sq     df          F        PR(>F)
         technique                     22.333355    2.0  76.430298  4.982920e-27
         text_size                      0.252107    1.0   1.725548  1.900955e-01
         distance                       0.035125    1.0   0.240415  6.243050e-01
         ordering                       4.042802    2.0  13.835474  1.904089e-06
         technique:text_size            0.650853    2.0   2.227382  1.097877e-01
         technique:distance             0.098190    2.0   0.336030  7.149003e-01
         text_size:distance             0.559213    1.0   3.827533  5.144784e-02
         technique:ordering             5.996749    4.0  10.261184  9.495336e-08
         technique:text_size:distance   0.854515    2.0   2.924364  5.540194e-02
         Residual                      39.447745  270.0        NaN           NaN
```

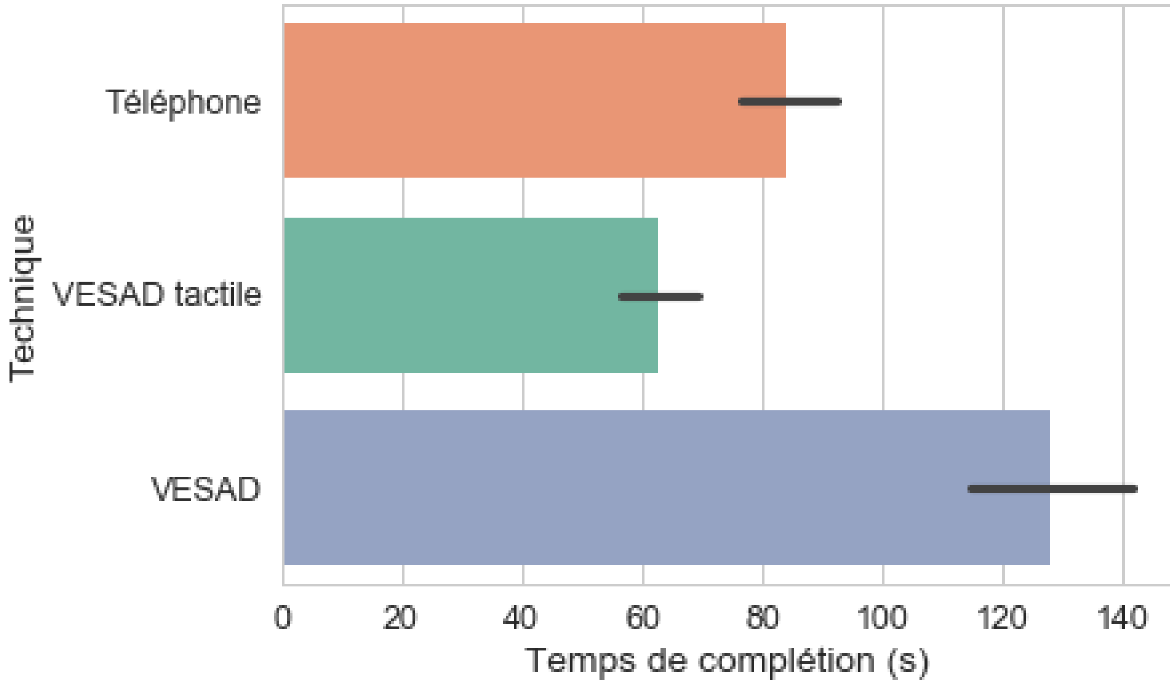
The main significant effect on TCT is TECHNIQUE ($F = 76.4$, $p < 0.0001$), then ORDERING ($F = 13.8$, $p < 0.0001$). There is also an significant interaction effect: TECHNIQUE x ORDERING ($F = 2.9$, $p < 0.0001$).

We display mean TCT values with 95% CI for these conditions:

```
In [56]: trial_means(['technique'], ['total_time'], aggregate=print_exp_mean_ci)
```

```
Out[56]:                Temps de complétion (s)
         Technique
         Téléphone         84.02 [76.81, 92.14]
         VESAD tactile     62.59 [56.10, 69.13]
         VESAD           127.71 [114.68, 143.47]
```

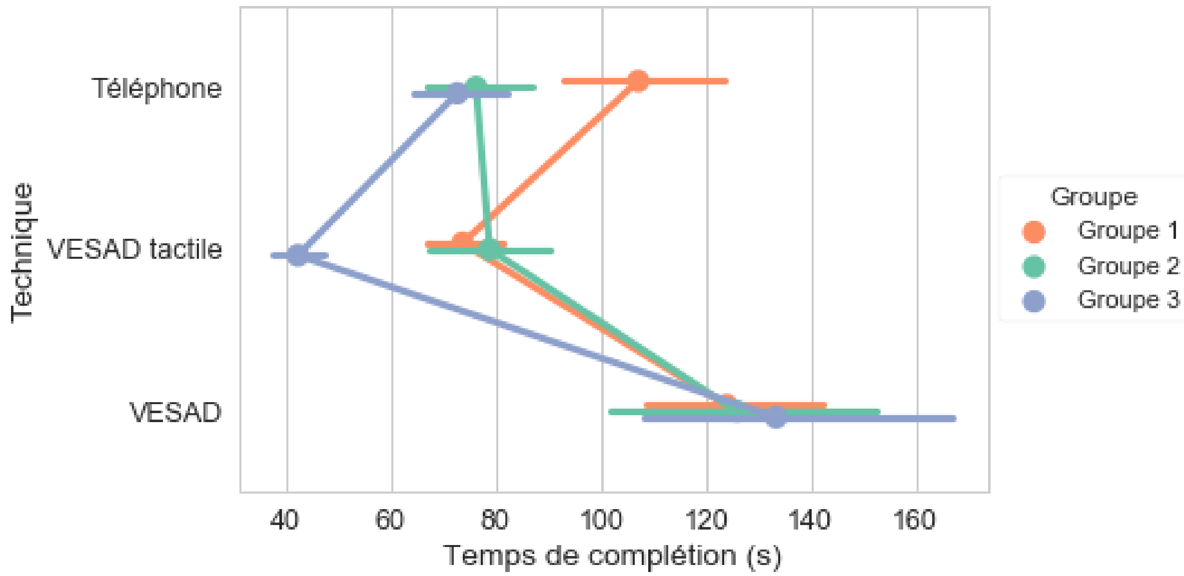
```
In [57]: ax = sns.barplot(x=trials_dvs['total_time'], y=technique['label'],
                          palette=technique['palette'], data=trials, estimator=exp_mean)
         ax.get_figure().savefig('tct.png')
```



In [58]:
```
trial_means(['ordering', 'technique'], ['total_time'],
            aggregate=print_exp_mean_ci).unstack()
```

Out[58]:
```
          Temps de complétion (s)                         \
Technique                Téléphone         VESAD tactile
Groupe
Groupe 1   107.14 [91.84, 123.42]  73.63 [66.95, 81.19]
Groupe 2     76.22 [66.67, 87.00]  78.79 [68.79, 90.48]
Groupe 3     72.64 [64.44, 81.78]  42.27 [37.47, 47.37]


Technique                     VESAD
Groupe
Groupe 1   124.00 [109.18, 141.63]
Groupe 2   125.91 [102.74, 154.53]
Groupe 3   133.41 [108.55, 167.96]
```

In [59]:
```
ax = sns.pointplot(x=trials_dvs['total_time'], y=technique['label'],
                   hue=ordering['label'], palette=ordering['palette'],
                   data=trials, dodge=True, estimator=exp_mean)
config_legend(ax, 'ordering')
ax.get_figure().savefig('tct_ordering.png')
```



It seems that participants who started with *PhoneOnly* were slower with this technique than the the other groups. Similarly, participants who finished with *PhoneInArOut* were faster with this technique. It indicates there is a learning curve on the task, but interestingly participants from all groups performed equally with *MidAirInArOut* technique.

We compare the TCT for the three techniques only with pairwise t-tests (Benjamini–Hochberg correction) .

```
In [60]: test_pairwise_trials('technique', 'total_time', correction_method='fdr_bh',
                              log_data=True)
```

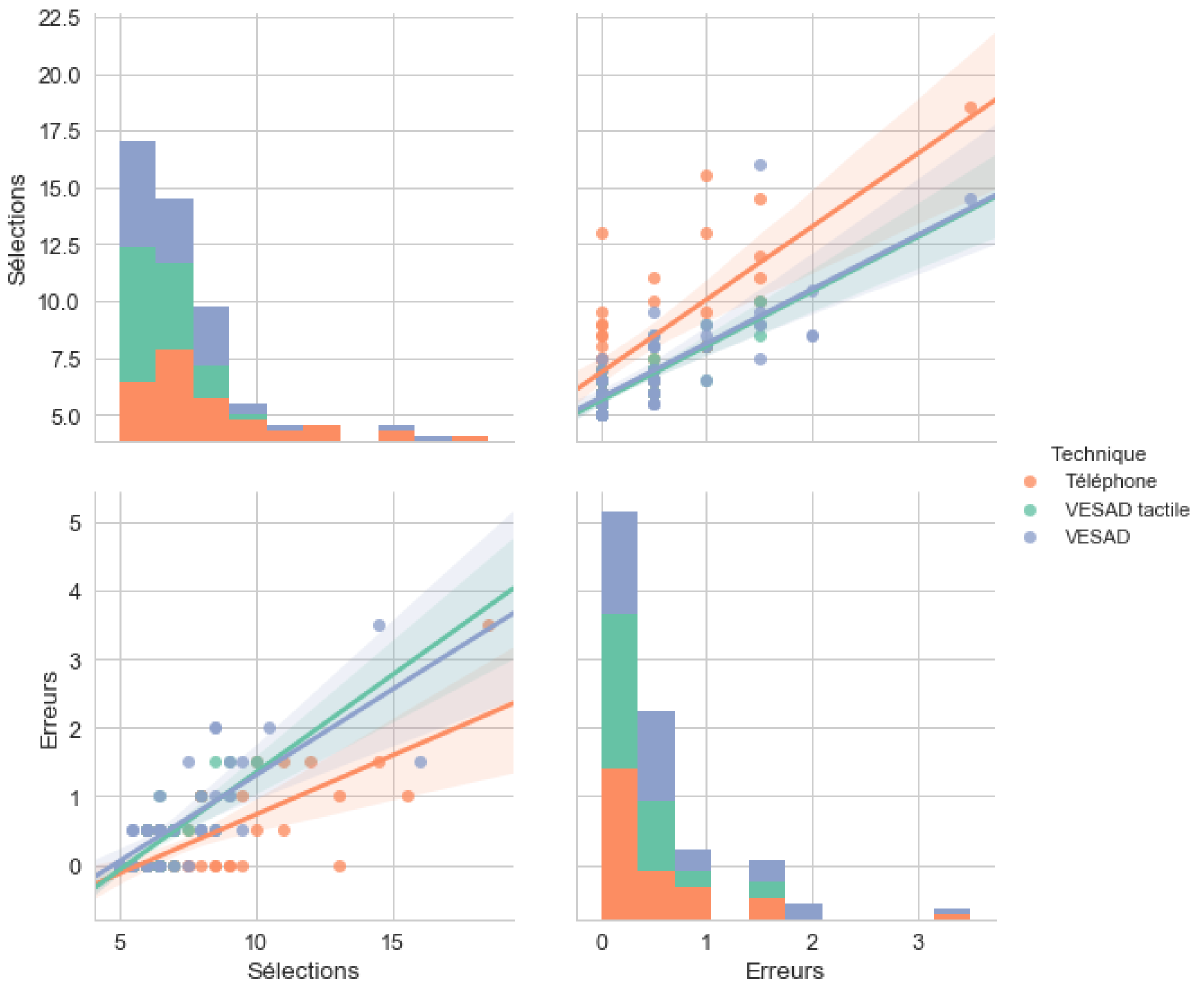
```
Out[60]:            VI     Valeur VI 1    Valeur VI 2                       VD  \
         0  Technique      Téléphone  VESAD tactile  Temps de complétion (s)
         1  Technique      Téléphone          VESAD  Temps de complétion (s)
         2  Technique  VESAD tactile          VESAD  Temps de complétion (s)

            Différence des moyennes  Différence des moyennes (%)  Statistique T  \
         0                21.840362                    32.666819       4.090635
         1               -49.467731                   -35.803106      -5.615875
         2               -71.308093                   -51.610437      -9.032751

                Valeur p
         0  9.077859e-05
         1  2.966612e-07
         2  6.282833e-14
```

- *PhoneInArOut* is 71s (+52%) faster than *MidAirInArOut* ($p < 0.0001$).
- *PhoneOnly* is 49s (+36%) faster than *MidAirInArOut* ($p < 0.0001$).
- *PhoneInArOut* is 22s (+33%) faster than *PhoneOnly* ($p < 0.0001$).

0.3.2 3.2. Errors

We visualize first the SELECTIONS and ERRORS distributions:

```
In [61]: g = sns.pairplot(trials, hue=technique['label'], kind='reg',
                          vars=[trials_dvs['selections_count'], trials_dvs['errors']],
                          palette=technique['palette'], size=4);
         g.savefig('selections_errors_distributions.png')
```



It seems that a user makes as much errors as she makes selections. The relation is almost the same for each technique, even if users seems to make more selections for the same number of errors with PhoneOnly.

We can't use ANOVA on SELECTIONS and ERRORS variables as their distributions are exponentials. We use instead the Kruskal-Wallis test (Benjamini–Hochberg correction) to check if there is significative differences due to TECHNIQUE, TEXT_SIZE, DISTANCE or ORDERING.

```
In [62]: test_non_normal_trials(['technique', 'text_size', 'distance', 'ordering'],
                                ['selections_count', 'errors'])
```

Out[62]:

	VI	VD	Kruskal-Wallis H	Valeur p
0	Technique	Sélections	15.125918	0.004155
1	Taille du texte	Sélections	0.003897	0.950224
2	Distance	Sélections	0.052701	0.935347
3	Groupe	Sélections	11.510535	0.010095

```
4        Technique     Erreurs           5.201541   0.148433
5   Taille du texte    Erreurs           0.103661   0.935347
6          Distance    Erreurs           0.201599   0.935347
7            Groupe    Erreurs          11.153096   0.010095
```

Only TECHNIQUE ($p = 0.004$) and ORDERING ($p = 0.01$) have a significant effect on SELECTIONS. But, only ORDERING ($p = 0.01$) have a significant effect on ERRORS.

We use then pairwise Mann-Whitney tests (Benjamini–Hochberg correction) for the significant questions above:

```
In [63]: test_pairwise_non_normal_trials(['technique', 'ordering'],
                                          ['selections_count', 'errors'])
```

```
Out[63]:            VI    Valeur VI 1    Valeur VI 2          VD  \
         0   Technique      Téléphone  VESAD tactile  Sélections
         1   Technique      Téléphone          VESAD  Sélections
         2   Technique  VESAD tactile          VESAD  Sélections
         3      Groupe       Groupe 1       Groupe 2  Sélections
         4      Groupe       Groupe 1       Groupe 3  Sélections
         5      Groupe       Groupe 2       Groupe 3  Sélections
         6   Technique      Téléphone  VESAD tactile     Erreurs
         7   Technique      Téléphone          VESAD     Erreurs
         8   Technique  VESAD tactile          VESAD     Erreurs
         9      Groupe       Groupe 1       Groupe 2     Erreurs
         10     Groupe       Groupe 1       Groupe 3     Erreurs
         11     Groupe       Groupe 2       Groupe 3     Erreurs

             Différence des moyennes  Différence des moyennes (%)  Mann-Whitney U  \
         0                  1.864583                    29.537954           627.0
         1                  1.041667                    14.598540           864.5
         2                 -0.822917                   -11.532847           915.0
         3                  1.729167                    26.265823           755.0
         4                  1.583333                    23.529412           755.0
         5                 -0.145833                    -2.167183          1136.0
         6                  0.125000                    42.857143          1083.5
         7                 -0.166667                   -28.571429           957.0
         8                 -0.291667                   -50.000000           873.0
         9                  0.333333                   103.225806           846.5
         10                 0.343750                   110.000000           761.5
         11                 0.010417                     3.333333          1039.0

             Valeur p
         0   0.000635
         1   0.029356
         2   0.059881
         3   0.005196
         4   0.005196
         5   0.454285
         6   0.312007
         7   0.083050
         8   0.026306
```

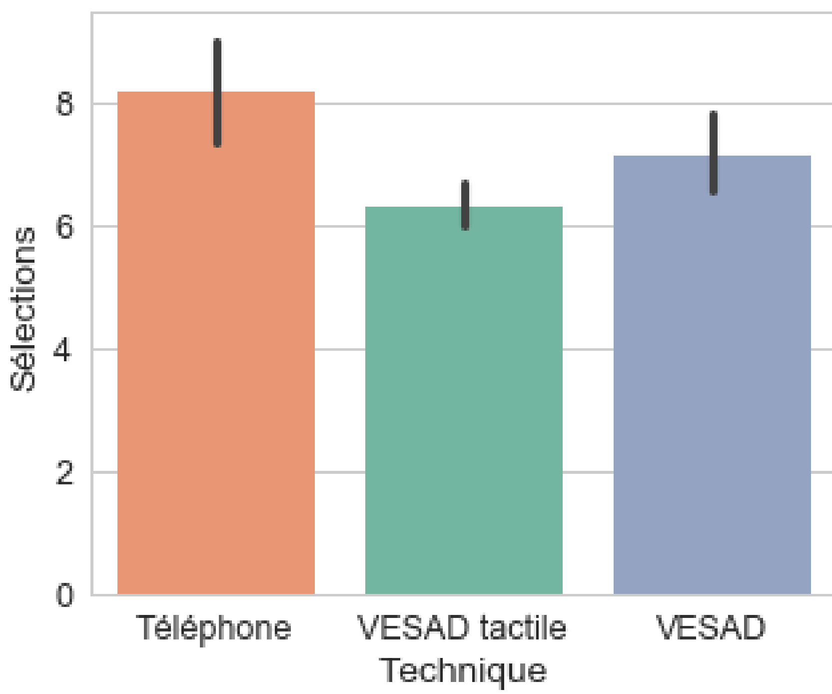
```
9    0.020183
10   0.005196
11   0.205336
```

In [64]:
```
trial_means(['technique'], ['selections_count', 'errors'])
```

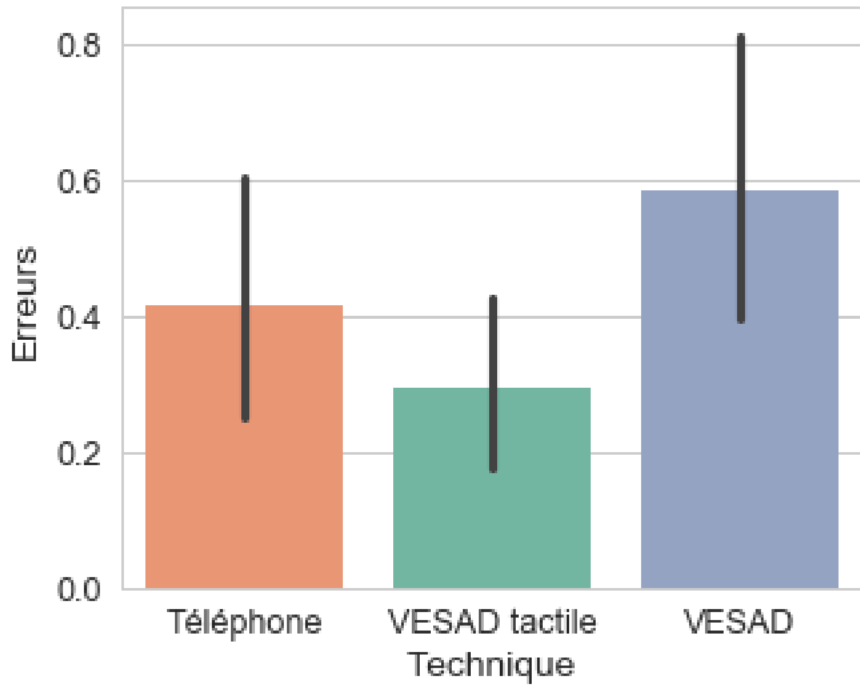
Out[64]:

Technique	Sélections	Erreurs
Téléphone	8.18 [7.42, 8.97]	0.42 [0.25, 0.59]
VESAD tactile	6.31 [5.99, 6.66]	0.29 [0.18, 0.42]
VESAD	7.14 [6.53, 7.78]	0.58 [0.40, 0.82]

In [65]:
```
(fig, axs) = plot_trials([['technique']], 'selections_count')
fig.savefig('selections.png')
```



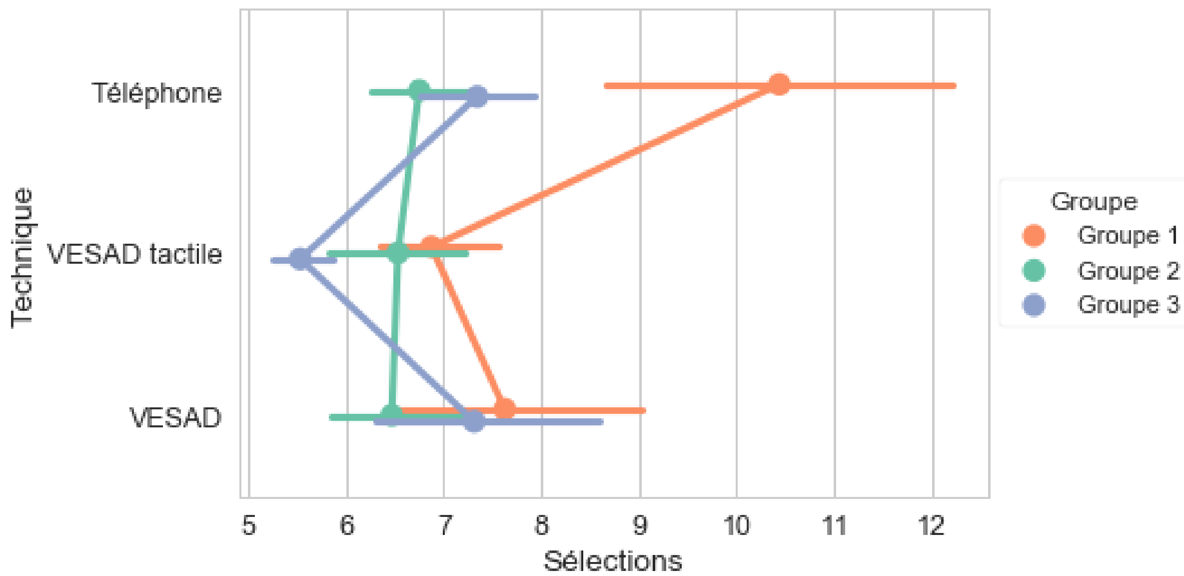
In [66]:
```
(fig, axs) = plot_trials([['technique']], 'errors')
fig.savefig('errors.png')
```



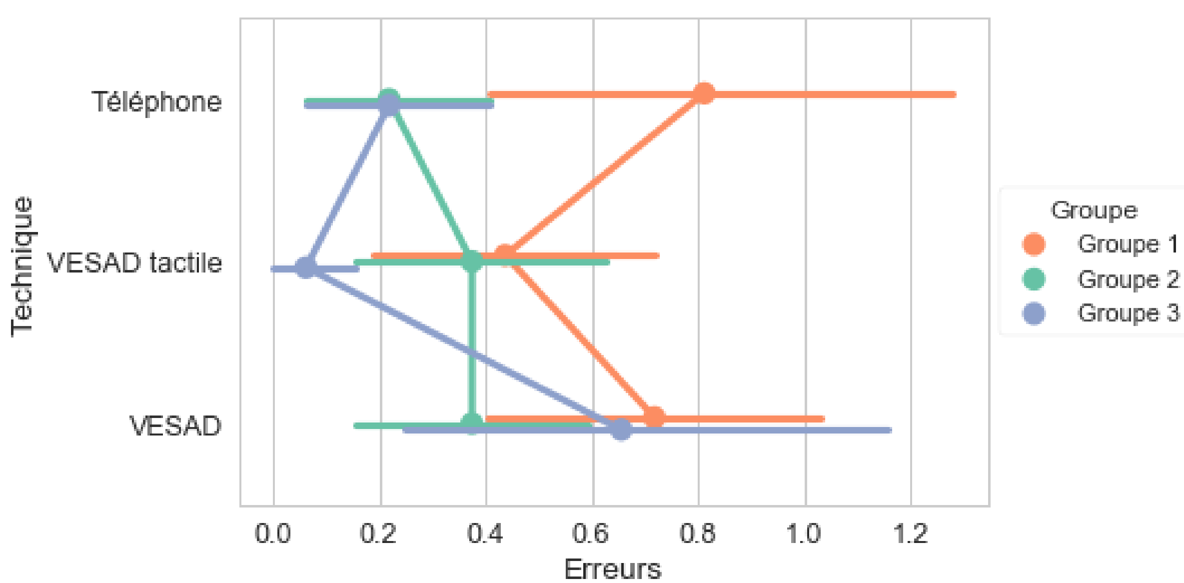

```
In [67]: trial_means(['ordering', 'technique'], ['selections_count', 'errors'])
```

```
Out[67]:                                  Sélections          Erreurs
         Groupe   Technique
         Groupe 1 Téléphone      10.44 [8.62, 12.38]  0.81 [0.38, 1.31]
                  VESAD tactile    6.88 [6.38, 7.56]  0.44 [0.19, 0.69]
                  VESAD            7.62 [6.53, 9.00]  0.72 [0.41, 1.03]
         Groupe 2 Téléphone        6.75 [6.25, 7.28]  0.22 [0.06, 0.41]
                  VESAD tactile    6.53 [5.84, 7.19]  0.38 [0.16, 0.62]
                  VESAD            6.47 [5.81, 7.19]  0.38 [0.19, 0.62]
         Groupe 3 Téléphone        7.34 [6.72, 8.00]  0.22 [0.06, 0.41]
                  VESAD tactile    5.53 [5.22, 5.84]  0.06 [0.00, 0.16]
                  VESAD            7.31 [6.22, 8.50]  0.66 [0.25, 1.12]
```

```
In [68]: ax = sns.pointplot(x=trials_dvs['selections_count'], y=technique['label'],
                            hue=ordering['label'], palette=ordering['palette'],
                            data=trials, dodge=True)
         config_legend(ax, 'ordering')
         ax.get_figure().savefig('selections_ordering.png')
```




```
In [69]: ax = sns.pointplot(x=trials_dvs['errors'], y=technique['label'],
                            hue=ordering['label'], palette=ordering['palette'],
                            data=trials, dodge=True)
         config_legend(ax, 'ordering')
         ax.get_figure().savefig('errors_ordering.png')
```



0.3.3 3.3. Navigation

Variable meanings:

- Selection Time = time spent looking for where to drop an item that had been picked

- Selection Distance = distance travelled by the finger with an item selected
- Head Phone Distance = sum of the distance between the head and the phone

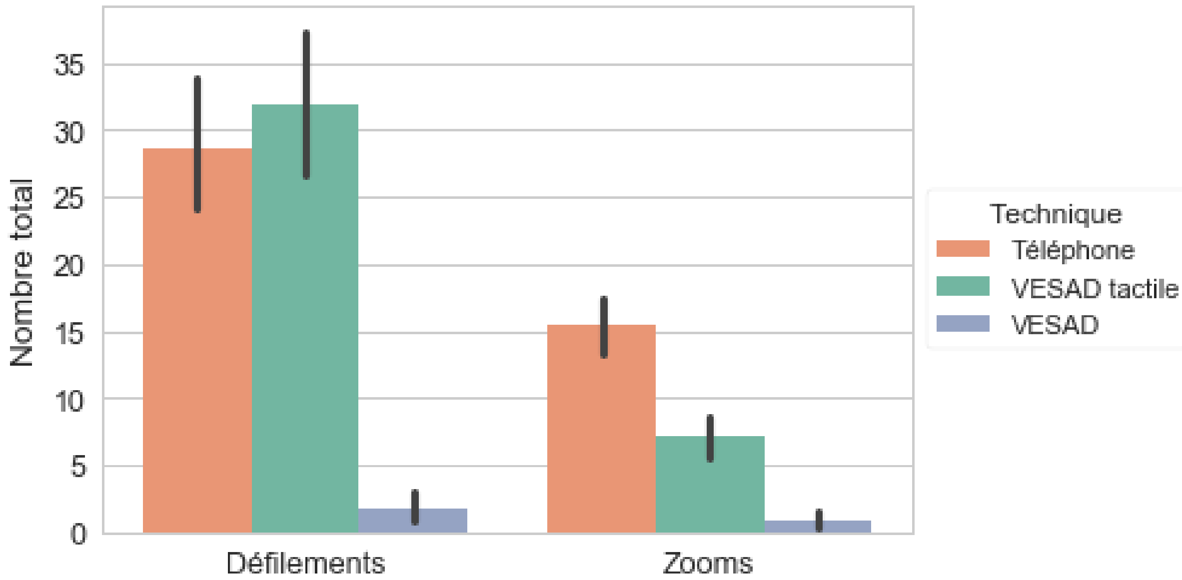
In [70]:
```
# Data preparation
trial_counts = melt_trials(var_name=labels['category'],
                           value_name=labels['count'],
                           value_vars=[trials_dvs['pan_count'],
                                       trials_dvs['zoom_count']])

trial_times = melt_trials(var_name=labels['category'],
                          value_name=labels['time'],
                          value_vars=[trials_dvs['selections_time'],
                                      trials_dvs['pan_time'],
                                      trials_dvs['zoom_time']])

trial_distances_dvs = [trials_dvs['selections_projected_distance'],
                       trials_dvs['pan_projected_distance'],
                       trials_dvs['zoom_projected_distance'],
                       trials_dvs['absolute_head_phone_distance']]
trial_distances = melt_trials(var_name=labels['category'],
                              value_name=labels['distance'],
                              value_vars=trial_distances_dvs)
```

In [71]:
```
trial_means(['technique'], ['pan_count', 'zoom_count'])
```

Out[71]:

Technique	Défilements	Zooms
Téléphone	28.70 [23.96, 34.15]	15.53 [13.66, 17.48]
VESAD tactile	31.81 [26.84, 37.13]	7.14 [5.73, 8.60]
VESAD	1.83 [0.81, 2.93]	0.83 [0.27, 1.49]

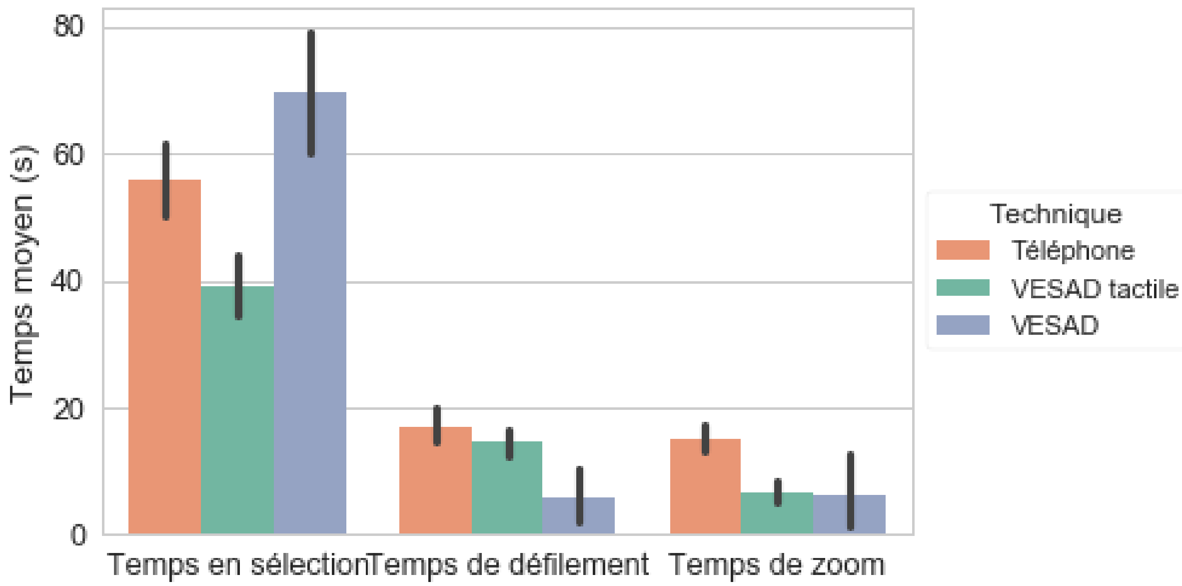
In [72]:
```
ax = sns.barplot(x=labels['category'], y=labels['count'],
                 hue=technique['label'], palette=technique['palette'],
                 data=trial_counts)
config_legend(ax, 'technique')
ax.set(xlabel='')
ax.get_figure().savefig('navigation_count.png')
```



In [73]:
```
trial_means(['technique'], ['selections_time', 'pan_time', 'zoom_time'])
```

Out[73]:
```
                 Temps en sélection   Temps de défilement  \
Technique
Téléphone       55.74 [50.09, 61.69]  17.12 [14.59, 19.82]
VESAD tactile   38.98 [34.28, 44.09]  14.53 [12.71, 16.61]
VESAD           69.68 [61.40, 78.83]    5.97 [2.18, 10.12]

                      Temps de zoom
Technique
Téléphone       15.18 [13.28, 17.19]
VESAD tactile      6.70 [5.06, 8.61]
VESAD             6.24 [1.56, 12.10]
```

In [74]:
```
ax = sns.barplot(x=labels['category'], y=labels['time'], data=trial_times,
                 hue=technique['label'], palette=technique['palette'])
config_legend(ax, 'technique')
ax.set(xlabel='')
ax.get_figure().savefig('navigation_time.png')
```




```
In [75]: trial_means(['technique'], ['selections_projected_distance',
                                     'pan_projected_distance',
                                     'zoom_projected_distance',
                                     'absolute_head_phone_distance'])

Out[75]:               Distance en sélection Distance de défilement   Distance de zoom  \
         Technique
         Téléphone        4.87 [4.06, 5.74]      1.50 [1.20, 1.83]  2.11 [1.75, 2.56]
         VESAD tactile    2.83 [2.38, 3.28]      1.09 [0.90, 1.28]  0.69 [0.51, 0.87]
         VESAD           8.72 [7.21, 10.56]      0.47 [0.19, 0.80]  0.62 [0.13, 1.21]

                       Mouvements tête-téléphone
         Technique
         Téléphone             3.18 [2.35, 4.16]
         VESAD tactile         1.57 [1.26, 1.92]
         VESAD                 6.12 [4.90, 7.48]

In [76]: g = sns.factorplot(x=technique['label'], y=labels['distance'],
                            col=labels['category'], data=trial_distances,
                            palette=technique['palette'], kind='bar', col_wrap=2)

         g.set_titles('{col_name}') # Replace subplot titles
         for ax in g.axes:
             ax.title.set_position([0.5, -0.12])

         g.set_axis_labels('') # Custom legend
         g.set_xticklabels([])
         legend_handles = [patches.Patch(color=color, label=value)\
                           for value, color in zip(technique['categorical'],
                                                   technique['palette'])]
```

```
legend = plt.legend(handles=legend_handles, loc='center left',
                    bbox_to_anchor=(1, 1.1), title=technique['label'])
fix_legend_fontsize(legend)

g.savefig('navigation_distance.png')
```