Importing Libraries

In [1]:
```python
# Importing libs
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from pathlib import Path
```

In [2]:
```python
# from IPython.display import display, HTML

# display(HTML("""
# <style>
# /* Import JetBrains Mono */
# @import url('https://fonts.googleapis.com/css2?family=JetBrains+Mono:wght@400;500

# /* Global notebook styling - added more specific selectors */
# body, .jp-Notebook, .jp-NotebookPanel, .container, #notebook-container {
#     font-family: 'JetBrains Mono', monospace !important;
#     font-size: 17px;
#     background-color: #0f1117 !important;
#     color: #e6e6e6 !important;
# }

# /* Code cells and outputs */
# code, pre, .jp-CodeMirror, .CodeMirror pre {
#     font-family: 'JetBrains Mono', monospace !important;
#     font-size: 16px !important;
# }

# /* Tables - Increased specificity to override default pandas/jupyter styles */
# .rendered_html table, table.dataframe {
#     border-collapse: collapse !important;
#     margin: 1em 0 !important;
#     font-size: 16px !important;
#     background-color: #161a23 !important;
#     border-radius: 10px !important;
#     overflow: hidden !important;
#     box-shadow: 0 8px 24px rgba(0,0,0,0.4) !important;
#     border: none !important;
# }

# /* Table header */
# .rendered_html thead th, .dataframe thead th {
#     background-color: #1f2430 !important;
#     color: #cdd6f4 !important;
#     padding: 12px 14px !important;
#     text-align: left !important;
#     font-weight: 600 !important;
#     border-bottom: 1px solid #2a2f3a !important;
# }

# /* Table body cells */
# .rendered_html tbody td, .dataframe tbody td {
```

```
#     padding: 10px 14px !important;
#     border-bottom: 1px solid #2a2f3a !important;
#     color: #e6e6e6 !important;
# }

# /* Zebra striping */
# .rendered_html tbody tr:nth-child(even) {
#     background-color: #141824 !important;
# }

# /* Row hover effect */
# .rendered_html tbody tr:hover {
#     background-color: #22273a !important;
# }

# /* Scrollbar styling */
# ::-webkit-scrollbar { width: 10px; height: 10px; }
# ::-webkit-scrollbar-track { background: #0f1117; }
# ::-webkit-scrollbar-thumb { background: #2a2f3a; border-radius: 6px; }
# </style>
# """))
```

In [3]:

```
# Setting global font
plt.rcParams['font.family'] = 'serif'
```

Data Loading

In [4]:

```
# Loading data
df = pd.read_csv("../data/raw/drug_data.csv")
df.head(3)
```

Out[4]:

	drug_name	medical_condition	medical_condition_description	activity	rx_otc	pregna
0	doxycycline	Acne	Acne Other names: Acne Vulgaris; Blackheads; B...	87%	Rx	
1	spironolactone	Acne	Acne Other names: Acne Vulgaris; Blackheads; B...	82%	Rx	
2	minocycline	Acne	Acne Other names: Acne Vulgaris; Blackheads; B...	48%	Rx	

General Considerations

In [5]:

```
# Code is Coming
```

Major Column Descriptors

activity: Indicates recent site visitor activity relative to other medications in the list. Data was gathered from Drugs.com .

rx_otc: Represents whether a drug requires a prescription (Rx) or is available over-the-counter (OTC).

OTC: Can be purchased without a prescription.

Rx: Prescription needed.

Rx/OTC: Available either by prescription or over-the-counter.

pregnancy_category: Classifies drugs based on safety during pregnancy:

A: Well-controlled studies show no fetal risk in the first trimester and no evidence of risk later.

B: Animal studies show no fetal risk; no adequate human studies.

C: Animal studies show fetal risk; no adequate human studies, but potential benefits may justify use.

D: Positive evidence of fetal risk in humans; potential benefits may justify use despite risks.

X: Evidence of fetal abnormalities or risk clearly outweighs potential benefits.

N: Not classified by the FDA.

csa: Controlled Substances Act (CSA) Schedule:

M: Multiple schedules depending on dosage or form.

U: CSA schedule unknown.

N: Not subject to the CSA.

1–5: Range of abuse potential, from high (1) to low (5), with associated medical use and dependence risk.

alcohol: Indicates interaction with alcohol: X = interacts with alcohol.

rating: User rating of medication effectiveness considering positive/adverse effects and ease of use. Scale: 1 = not effective, 10 = most effective.

I focused on pain and cold medications for a deeper analysis because they are among the most commonly used drugs.

Handling Missing Data

In [6]:

```
# Missing data
df.isna().sum()/len(df)*100
```

Out[6]:
```
drug_name                         0.000000
medical_condition                 0.000000
medical_condition_description     0.000000
activity                          0.000000
rx_otc                            0.025259
pregnancy_category                6.289467
csa                               0.000000
alcohol                          49.709523
rating                           46.526901
no_of_reviews                    46.526901
medical_condition_url             0.000000
drug_link                         0.000000
dtype: float64
```

Since alcohol, rating, and number of reviews have a high percentage of missing values, they will be excluded from the analysis. For pregnancy_category, missing values will be imputed using the mode.

In [7]:
```
df.groupby('pregnancy_category').size()
```

Out[7]:
```
pregnancy_category
A      19
B     719
C    1889
D     339
N     600
X     144
dtype: int64
```

Here, we observe that category C is the most common, so we will replace all missing values with C.

For the Rx/OTC category, some drugs may be available OTC in small doses but require a prescription in larger doses. Therefore, all Rx/OTC drugs will be considered as OTC.

In [8]:
```
# Replacements
df['pregnancy_category'] = df['pregnancy_category'].fillna('C')
df['rx_otc'] = df['rx_otc'].replace('Rx/OTC', 'OTC')
df['rx_otc'] = df['rx_otc'].fillna('Rx')
```

In [9]:
```
# Checking rx_otc column
df.groupby('rx_otc').size()
```

Out[9]:
```
rx_otc
OTC    1257
Rx     2702
dtype: int64
```

In [10]:
```
# Drops
cols_to_drop = ['alcohol', 'rating', 'no_of_reviews']
cols_existing = [col for col in cols_to_drop if col in df.columns]
df.drop(columns=cols_existing, inplace=True)
```

In [11]:
```python
# Checking Missing
df.isna().sum()/len(df)*100
```

Out[11]:
```
drug_name                         0.0
medical_condition                 0.0
medical_condition_description     0.0
activity                          0.0
rx_otc                            0.0
pregnancy_category                0.0
csa                               0.0
medical_condition_url             0.0
drug_link                         0.0
dtype: float64
```

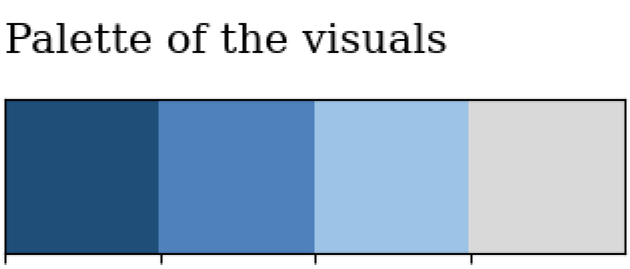
In [12]:
```python
# Path
output_path = Path("../data/processed/drug_data_processed.csv")

# Export
df.to_csv(output_path, index=False)

print("Processed data saved to:", output_path)
```

```
Processed data saved to: ..\data\processed\drug_data_processed.csv
```

No missing data remains; we can now proceed with visualization.

Data Visualization

In [13]:
```python
# Palette
colors = ['#1f4e79', '#4f81bd', '#9dc3e6', '#d9d9d9']

sns.palplot(colors)
plt.title("Palette of the visuals",loc='left',fontfamily='Serif',fontsize=15,y=1.2)
plt.show()
```



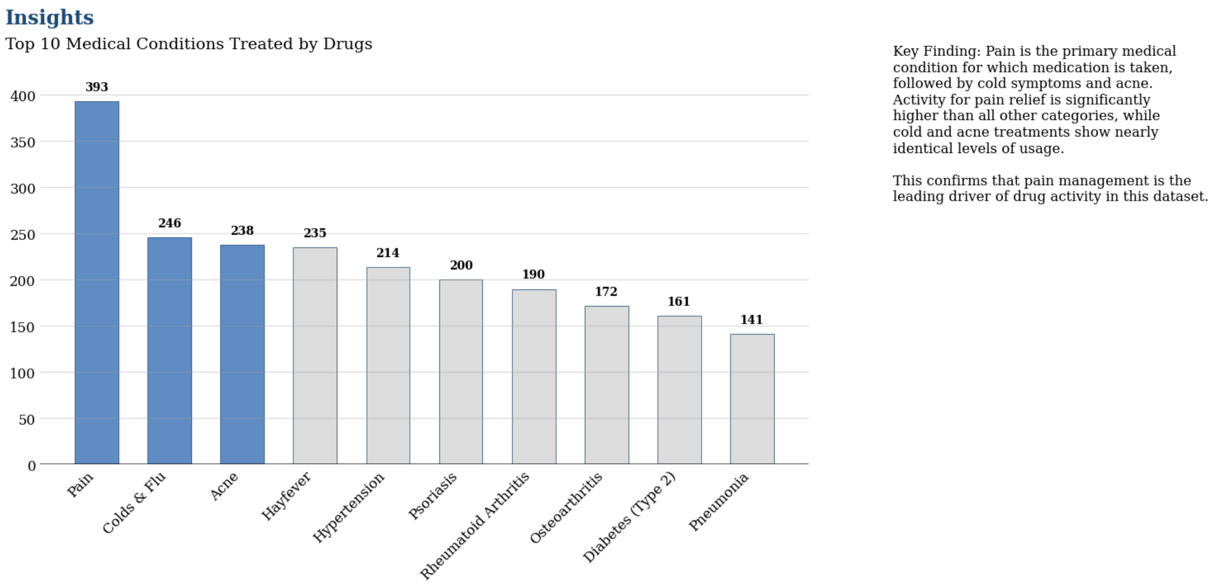
In [14]:
```python
# Lets get insights from medical_condition column
common_drugs = df.groupby('medical_condition').size().sort_values(ascending=False)
top_common_drugs = common_drugs.head(10)
top_common_drugs
```

Out[14]:
```
medical_condition
Pain                      393
Colds & Flu               246
Acne                      238
Hayfever                  235
Hypertension              214
Psoriasis                 200
Rheumatoid Arthritis      190
Osteoarthritis            172
Diabetes (Type 2)         161
Pneumonia                 141
dtype: int64
```

The most common medical conditions treated with these drugs are listed

In [15]:
```python
# Colors '#1f4e79', '#4f81bd', '#9dc3e6', '#d9d9d9'

color_map = ['#d9d9d9'] * len(top_common_drugs)
color_map[:3] = ['#4f81bd'] * 3

fig, ax = plt.subplots(figsize=(12, 6))

ax.bar(
    top_common_drugs.index,
    top_common_drugs,
    color=color_map,
    alpha=0.9,
    width=0.6,
    linewidth=0.6,
    edgecolor='#1f4e79'
)

# Text
fig.text(0.09, 1,
         'Insights',
         fontfamily='Serif',
         fontweight='bold',
         fontsize=17,
         color='#1f4e79'
        )
fig.text(0.09, 0.95,
         'Top 10 Medical Conditions Treated by Drugs',
         fontfamily='Serif',
         fontweight='light',
         fontsize=14
        )
fig.text(0.95, 0.61, '''
        Key Finding: Pain is the primary medical
        condition for which medication is taken,
        followed by cold symptoms and acne.
        Activity for pain relief is significantly
        higher than all other categories, while
        cold and acne treatments show nearly
        identical levels of usage.
```

```
        This confirms that pain management is the
        leading driver of drug activity in this dataset.
    '''
        ,fontsize=12,
        fontweight='light',
        fontfamily='serif'
    )

# X ticks
ax.tick_params(axis='x', labelrotation=45)
for label in ax.get_xticklabels():
    label.set_fontfamily('serif')
    label.set_ha('right')

# Annotations
for i in top_common_drugs.index:
    ax.annotate(f"{top_common_drugs[i]}",
                xy=(i, top_common_drugs[i]+15),
                 va = 'center', ha='center',
                 fontweight='bold',
                 fontfamily='serif',
                 fontsize=10
                )

# Remove spines
for s in ['top', 'right', 'left', 'bottom']:
    ax.spines[s].set_visible(False)

# Remove axis tick dashes (the "-" you see)
ax.tick_params(axis=u'both', which=u'both',length=0)

# Baseline
ax.axhline(y=0, color='black', linewidth=1.3, alpha=0.7)

# Grid
ax.grid(axis='y', alpha=0.4)

ax.tick_params(axis='both', which='major', labelsize=12)
```



Since drugs used to treat pain (painkillers) are widely used, their activity, tolerance, and pregnancy safety should be examined.

In [16]:
```
pain_drugs = df[df['medical_condition'] == 'Pain']
pain_drugs.head(3)
```

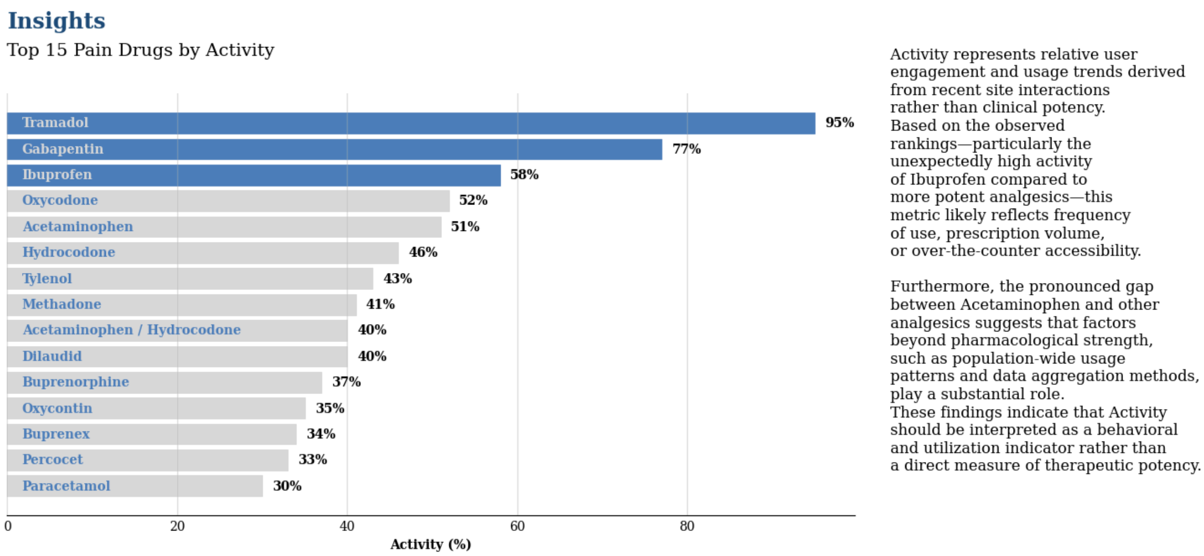
Out[16]:

	drug_name	medical_condition	medical_condition_description	activity	rx_otc	pregn
2745	tramadol	Pain	Pain An unpleasant sensory and emotional exper...	95%	Rx	
2746	gabapentin	Pain	Pain An unpleasant sensory and emotional exper...	77%	Rx	
2747	ibuprofen	Pain	Pain An unpleasant sensory and emotional exper...	58%	OTC	

In [17]:
```
top_pain_drugs = pain_drugs.head(15).copy()
top_pain_drugs.loc[:, 'activity'] = pd.to_numeric(
    top_pain_drugs['activity'].astype(str).str.replace('%', ''),
    errors='coerce'
)
top_pain_drugs = top_pain_drugs.sort_values(by='activity', ascending=False)
top_pain_drugs.loc[:, 'drug_name'] = top_pain_drugs['drug_name'].str.title()

color_map = ['#d9d9d9'] * len(top_pain_drugs)
color_map[:3] = ['#4f81bd'] * 3

text_color_map = ['#4f81bd'] * len(top_pain_drugs)
text_color_map[:3] = ['#d9d9d9'] * 3

fig, ax = plt.subplots(1,1, figsize=(12,6))

bars = ax.barh(top_pain_drugs['drug_name'],top_pain_drugs['activity'], linewidth=0.
for i, bar in enumerate(bars):
```

```python
    width = bar.get_width()
    label = top_pain_drugs['drug_name'].iloc[i]

    bar.set_color(color_map[i])

    ax.annotate(
        label,
        xy=(1, bar.get_y() + bar.get_height()/2),
        xytext=(5, 0),
        textcoords="offset points",
        va='center',
        ha='left',
        fontsize=10,
        color=text_color_map[i],
        fontweight='bold',
        fontfamily='serif'
    )

    activity_value = top_pain_drugs['activity'].iloc[i]

    ax.annotate(
        f'{activity_value}%',
        xy=(activity_value, bar.get_y() + bar.get_height()/2),
        xytext=(8, 0),
        textcoords="offset points",
        va='center', ha='left',
        fontsize=10,
        color='black',
        fontweight='bold',
        fontfamily='serif'
    )

fig.text(0.125, 1, 'Insights', fontfamily='Serif', fontweight='bold', fontsize=17,
fig.text(0.125, 0.95, 'Top 15 Pain Drugs by Activity', fontfamily='Serif', fontweig
fig.text(0.915, 0.16, '''
    Activity represents relative user
    engagement and usage trends derived
    from recent site interactions
    rather than clinical potency.
    Based on the observed
    rankings—particularly the
    unexpectedly high activity
    of Ibuprofen compared to
    more potent analgesics—this
    metric likely reflects frequency
    of use, prescription volume,
    or over-the-counter accessibility.

    Furthermore, the pronounced gap
    between Acetaminophen and other
    analgesics suggests that factors
    beyond pharmacological strength,
    such as population-wide usage
    patterns and data aggregation methods,
    play a substantial role.
    These findings indicate that Activity
```

```
    should be interpreted as a behavioral
    and utilization indicator rather than
    a direct measure of therapeutic potency.
    '''
    ,fontsize=12, fontweight='light', fontfamily='serif'
)

spines = ['top', 'left', 'right']
for i in spines:
    ax.spines[i].set_visible(False)

ax.set_yticklabels([])
ax.tick_params(axis=u'both', which=u'both',length=0)

ax.grid(axis='x', alpha=0.4)

ax.set_xlabel('Activity (%)',fontfamily='serif', fontweight='bold')
ax.set_title('')
ax.invert_yaxis()
```

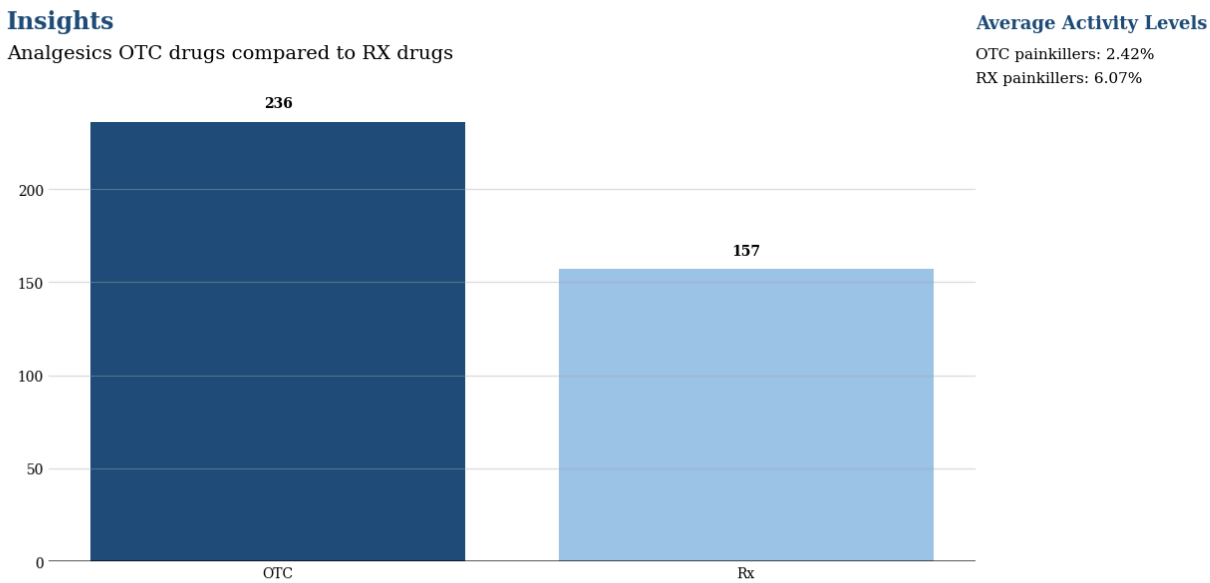


Let's examine the number of OTC and Rx drugs among pain medications and see what insights we can derive from them.

In [18]:
```
pain_drugs.loc[:, 'activity'] = pd.to_numeric(
    pain_drugs['activity'].astype(str).str.replace('%', ''),
    errors='coerce'
)

pain_otc_rx = pain_drugs.groupby('rx_otc')['activity'].agg(['count', 'mean'])

pain_otc_rx.columns = ['Total Drugs', 'Average Activity (%)']
```

In [19]:
```
# Colors '#1f4e79', '#4f81bd', '#9dc3e6', '#d9d9d9'
fig, ax = plt.subplots(1,1, figsize=(12,6))
color_map = ['#1f4e79','#9dc3e6']

ax.bar(pain_otc_rx.index, pain_otc_rx['Total Drugs'], color=color_map)
```

```
fig.text(0.09,1,"Insights",color='#1f4e79', fontfamily='serif', fontweight='bold',
fig.text(0.09,0.95,"Analgesics OTC drugs compared to RX drugs", fontfamily='serif',
fig.text(
    0.9, 1,
    "Average Activity Levels",
    fontsize=13,
    fontfamily='serif',
    fontweight="bold",
    color="#1f4e79"
)
fig.text(
    0.9, 0.95,
    f"OTC painkillers: {pain_otc_rx.iloc[0]['Average Activity (%)']:.2f}%",
    fontsize=11,
    fontfamily='serif'
)
fig.text(
    0.9, 0.91,
    f"RX painkillers: {pain_otc_rx.iloc[1]['Average Activity (%)']:.2f}%",
    fontsize=11,
    fontfamily='serif'
)

spines = ['top', 'bottom', 'left', 'right']
for s in spines:
    ax.spines[s].set_visible(False)

for i in pain_otc_rx.index:
    ax.annotate(
        f"{pain_otc_rx.loc[i, 'Total Drugs']}",
        xy=(i, pain_otc_rx.loc[i, 'Total Drugs'] + 10),
        ha='center',
        va='center',
        fontfamily='serif',
        fontweight='bold'
    )

for label in ax.get_yticklabels():
    label.set_fontname('serif')

for label in ax.get_xticklabels():
    label.set_fontname('serif')

ax.tick_params(axis=u'both', which=u'both',length=0)

ax.axhline(y=0, color='black', linewidth=1.3, alpha=0.7)

ax.grid(axis='y', alpha=0.4)
```



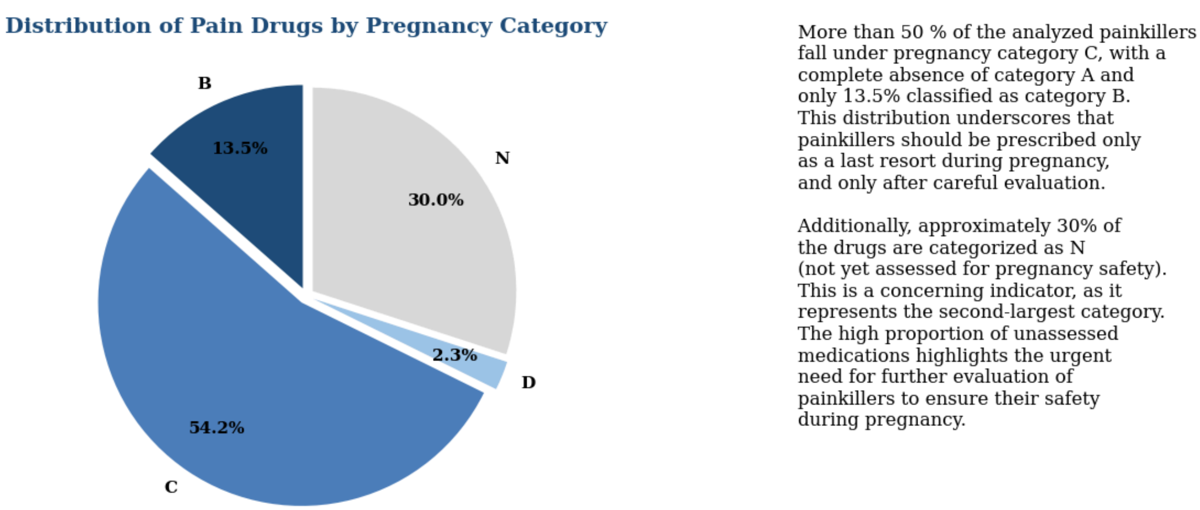
Let's examine the distribution of pregnancy categories among pain medications and see what insights we can derive from them.

In [20]:
```
pain_preg = pain_drugs.groupby('pregnancy_category')['pregnancy_category'].agg(['co
pain_preg.columns = ['Number of drugs']
```

In [21]:
```
fig, ax = plt.subplots(1,1, figsize=(12,6))
color_map =['#1f4e79', '#4f81bd', '#9dc3e6', '#d9d9d9']

explode = [0.04] * len(pain_preg)

ax.pie(
    pain_preg['Number of drugs'],
    labels=pain_preg.index,
    autopct='%1.1f%%',
    startangle=90,
    explode=explode,
    colors=color_map,
    textprops={
        'fontfamily': 'serif',
        'fontweight': 'bold',
        'fontsize': 11
    },
    pctdistance=0.75
)

fig.text(0.85, 0.265, '''
        More than 50 % of the analyzed painkillers
        fall under pregnancy category C, with a
        complete absence of category A and
        only 13.5% classified as category B.
        This distribution underscores that
        painkillers should be prescribed only
        as a last resort during pregnancy,
        and only after careful evaluation.

        Additionally, approximately 30% of
```

```
        the drugs are categorized as N
        (not yet assessed for pregnancy safety).
        This is a concerning indicator, as it
        represents the second-largest category.
        The high proportion of unassessed
        medications highlights the urgent
        need for further evaluation of
        painkillers to ensure their safety
        during pregnancy.
        '''
        , fontsize=12, fontweight='light', fontfamily='serif'
    )

ax.set_title("Distribution of Pain Drugs by Pregnancy Category", fontfamily='serif'
```

Out[21]: `Text(0.5, 1.0, 'Distribution of Pain Drugs by Pregnancy Category')`



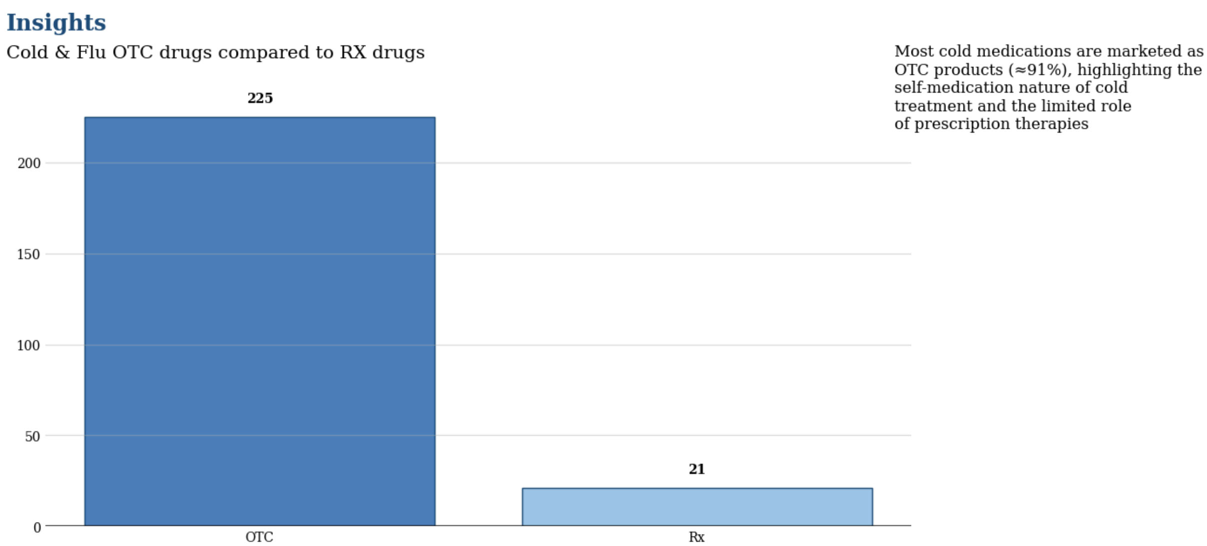
Now, let's examine cold and flu medications and see what insights we can gain.

Next, we will examine the distribution of OTC and Rx drugs to understand their prevalence and any patterns in usage.

In [22]:
```
cold_drugs = df[df['medical_condition']=='Colds & Flu']
otc_rx_cold_drugs = cold_drugs.groupby('rx_otc')[['rx_otc']].count()
otc_rx_cold_drugs.columns = ['count']
```

In [23]:
```
fig, ax = plt.subplots(1,1, figsize=(12,6))
color_map =['#1f4e79', '#4f81bd', '#9dc3e6', '#d9d9d9']

ax.bar(otc_rx_cold_drugs.index, otc_rx_cold_drugs['count'], edgecolor='#1f4e79', co

spines = ['top', 'bottom', 'left', 'right']
for s in spines:
    ax.spines[s].set_visible(False)

ax.axhline(color='black', alpha=0.4, linewidth=1.3)
```

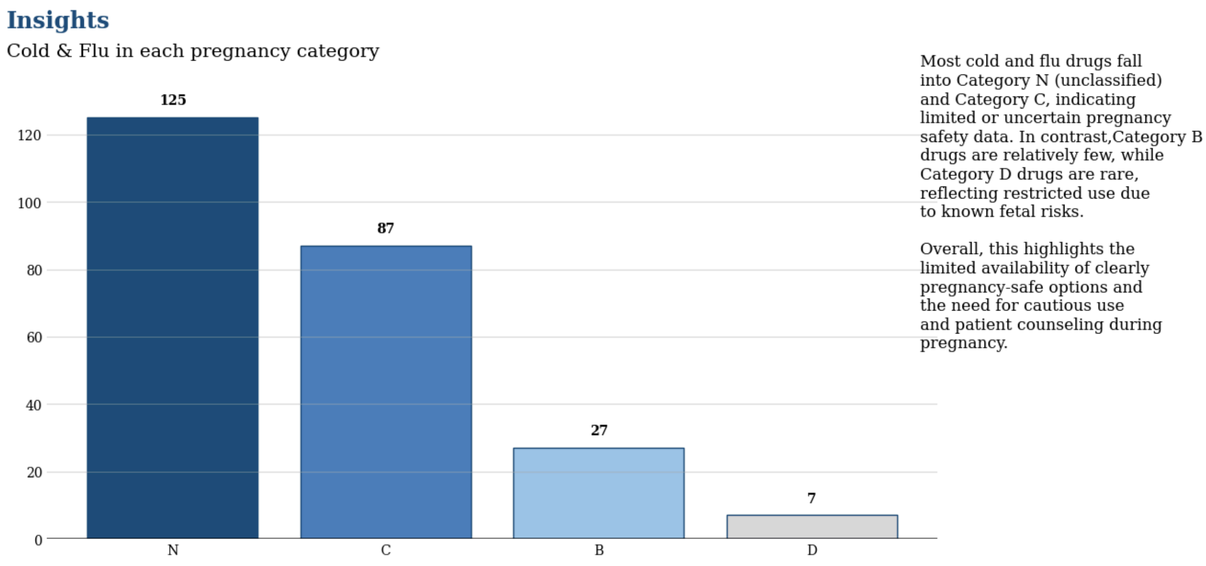
```python
for i in otc_rx_cold_drugs.index:
    ax.annotate(
        f"{otc_rx_cold_drugs['count'][i]}",
        xy=(i, otc_rx_cold_drugs['count'][i] + 10),
        ha='center',
        va='center',
        fontfamily='serif',
        fontweight='bold'
    )

fig.text(0.85, 0.79, '''
        Most cold medications are marketed as
        OTC products (≈91%), highlighting the
        self-medication nature of cold
        treatment and the limited role
        of prescription therapies
        '''
        , fontsize=12, fontweight='light', fontfamily='serif'
    )
fig.text(0.09,1,"Insights",color='#1f4e79', fontfamily='serif', fontweight='bold',
fig.text(0.09,0.95,"Cold & Flu OTC drugs compared to RX drugs", fontfamily='serif',

ax.tick_params(axis=u'both', which=u'both',length=0)

for label in ax.get_yticklabels():
    label.set_fontname('serif')

for label in ax.get_xticklabels():
    label.set_fontname('serif')

ax.axhline(y=0, color='black', linewidth=1.3, alpha=0.7)

ax.grid(axis='y', alpha=0.4)
```



Next, we will examine the distribution of pregnancy categories to understand their prevalence and any patterns in usage.

In [24]:
```python
cold_preg_drugs = cold_drugs.groupby('pregnancy_category')['pregnancy_category'].ag
```

In [25]:
```python
fig, ax = plt.subplots(1,1, figsize=(12,6))

color_map =['#1f4e79', '#4f81bd', '#9dc3e6', '#d9d9d9']

ax.bar(cold_preg_drugs.index, cold_preg_drugs['count'], color=color_map, edgecolor=

spines = ['top','bottom', 'left', 'right']
for s in spines:
    ax.spines[s].set_visible(False)

ax.tick_params(length=0, which=u"both", axis=u"both")

for label in ax.get_yticklabels():
    label.set_fontname('serif')

for label in ax.get_xticklabels():
    label.set_fontname('serif')

for x, val in enumerate(cold_preg_drugs['count']):
    ax.annotate(
        f"{val}",
        xy=(x, val + 5),
        ha='center',
        va='center',
        fontweight='bold',
        fontfamily='serif'
    )

fig.text(0.85, 0.41, '''
        Most cold and flu drugs fall
        into Category N (unclassified)
        and Category C, indicating
        limited or uncertain pregnancy
        safety data. In contrast,Category B
        drugs are relatively few, while
        Category D drugs are rare,
        reflecting restricted use due
        to known fetal risks.

        Overall, this highlights the
        limited availability of clearly
        pregnancy-safe options and
        the need for cautious use
        and patient counseling during
        pregnancy.
        '''
        , fontsize=12, fontweight='light', fontfamily='serif'
    )

fig.text(0.09,1,"Insights",color='#1f4e79', fontfamily='serif', fontweight='bold',
fig.text(0.09,0.95,"Cold & Flu in each pregnancy category", fontfamily='serif', fon

ax.axhline(y=0, color='black', linewidth=1.3, alpha=0.7)

ax.grid(alpha=0.4, axis='y')
```



Next, we will explore other medical conditions to uncover patterns and insights across different drug categories.

In [26]:

```
other_df = df[~df['medical_condition'].isin(['Colds & Flu', 'Pain'])]
```

Next, we will explore pregnancy categories across other medical conditions to identify patterns and insights.

In [27]:

```
other_preg = (
    other_df
    .groupby(['medical_condition', 'pregnancy_category'])
    .size()
    .unstack(fill_value=0)
)

other_preg = other_preg.loc[
    other_preg.sum(axis=1).sort_values(ascending=False).head(10).index
]
```

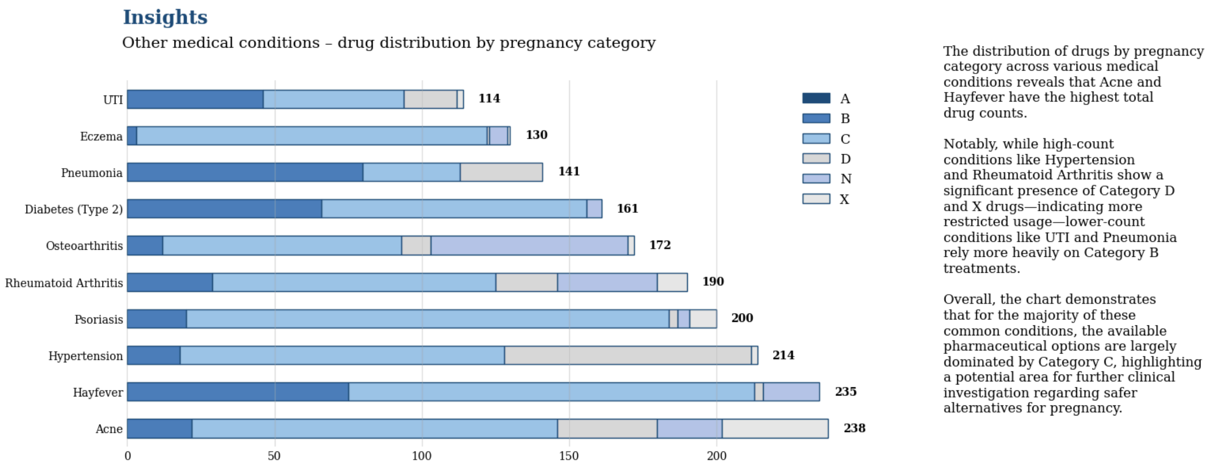
In [28]:

```
fig, ax = plt.subplots(1, 1, figsize=(12,6))

color_map = ['#1f4e79', '#4f81bd', '#9dc3e6', '#d9d9d9', '#b4c7e7', '#e7e6e6']

other_preg.plot(
    kind='barh',
    stacked=True,
    ax=ax,
    color=color_map,
    edgecolor='#1f4e79'
)

for s in ['top','bottom','left','right']:
    ax.spines[s].set_visible(False)

ax.tick_params(length=0, which='both')
ax.grid(axis='x', alpha=0.4)
```

```python
for label in ax.get_xticklabels() + ax.get_yticklabels():
    label.set_fontname('serif')

ax.set_xlabel('', fontfamily='serif')
ax.set_ylabel('', fontfamily='serif')

for y_pos, row in enumerate(other_preg.values):
    total = row.sum()
    ax.annotate(
        f"{total}",
        xy=(total + 5, y_pos),
        va='center',
        ha='left',
        fontfamily='serif',
        fontsize=10,
        fontweight='bold'
    )

fig.text(0.95, 0.15, '''
        The distribution of drugs by pregnancy
        category across various medical
        conditions reveals that Acne and
        Hayfever have the highest total
        drug counts.

        Notably, while high-count
        conditions like Hypertension
        and Rheumatoid Arthritis show a
        significant presence of Category D
        and X drugs—indicating more
        restricted usage—lower-count
        conditions like UTI and Pneumonia
        rely more heavily on Category B
        treatments.

        Overall, the chart demonstrates
        that for the majority of these
        common conditions, the available
        pharmaceutical options are largely
        dominated by Category C, highlighting
        a potential area for further clinical
        investigation regarding safer
        alternatives for pregnancy.
        '''
        , fontsize=12, fontweight='light', fontfamily='serif'
    )

fig.text(0.12, 1, "Insights",
         color='#1f4e79', fontfamily='serif',
         fontweight='bold', fontsize=17)

fig.text(0.12, 0.95,
         "Other medical conditions - drug distribution by pregnancy category",
         fontfamily='serif', fontweight='light', fontsize=14)
```

```
ax.legend(
    title='',
    frameon=False,
    prop={'family': 'serif', 'size': 12},
)
```

Out[28]: <matplotlib.legend.Legend at 0x18b40d5fb60>



Next, we will explore the distribution of OTC and Rx drugs across other medical conditions to identify patterns and insights.

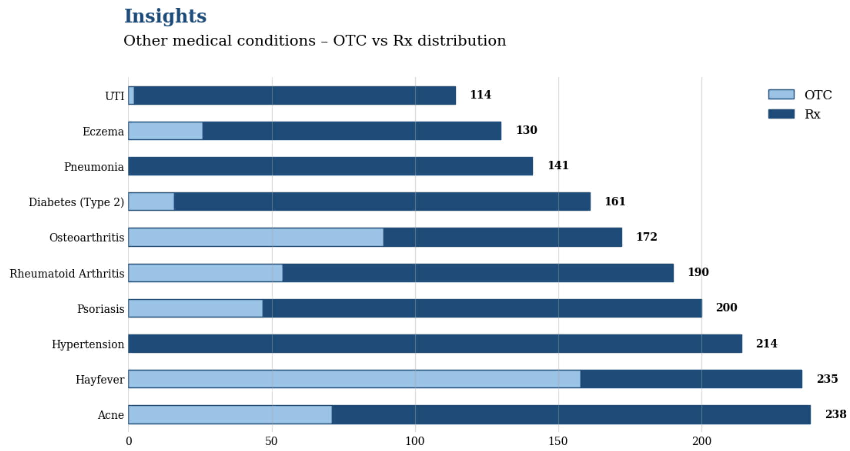
In [29]:
```
other_otc_rx = (
    other_df
    .groupby(['medical_condition', 'rx_otc'])
    .size()
    .unstack(fill_value=0)
)

other_otc_rx = other_otc_rx.loc[
    other_otc_rx.sum(axis=1).sort_values(ascending=False).head(10).index
]
```

In [30]:
```
fig, ax = plt.subplots(1, 1, figsize=(12,6))

# Palette aligned with your style
color_otc = '#9dc3e6'
color_rx  = '#1f4e79'

other_otc_rx[['OTC','Rx']].plot(
    kind='barh',
    stacked=True,
    ax=ax,
    color=[color_otc, color_rx],
    edgecolor='#1f4e79'
)

for s in ['top','bottom','left','right']:
    ax.spines[s].set_visible(False)

ax.tick_params(length=0, which='both')
ax.grid(axis='x', alpha=0.4)
```

```python
for label in ax.get_xticklabels() + ax.get_yticklabels():
    label.set_fontname('serif')

ax.set_xlabel('', fontfamily='serif')
ax.set_ylabel('', fontfamily='serif')

for y_pos, row in enumerate(other_otc_rx.values):
    total = row.sum()
    ax.annotate(
        f"{total}",
        xy=(total + 5, y_pos),
        va='center',
        ha='left',
        fontfamily='serif',
        fontsize=10,
        fontweight='bold'
    )

fig.text(0.94, 0.68, '''
        There is a profound reliance on Prescription
        (Rx) medications across almost all conditions.
        While Hayfever and Osteoarthritis show
        significant Over-the-Counter (OTC)
        accessibility, complex conditions like
        Diabetes and Pneumonia are managed
        almost exclusively through regulated
        prescriptions.
        '''
        , fontsize=12, fontweight='light', fontfamily='serif'
    )

fig.text(0.12, 1, "Insights",
         color='#1f4e79', fontfamily='serif',
         fontweight='bold', fontsize=17)

fig.text(0.12, 0.95,
         "Other medical conditions - OTC vs Rx distribution",
         fontfamily='serif', fontweight='light', fontsize=14)

ax.legend(
    title='',
    frameon=False,
    prop={'family': 'serif', 'size': 12},
)
```

Out[30]:

```
<matplotlib.legend.Legend at 0x18b423b0830>
```



There is a profound reliance on Prescription (Rx) medications across almost all conditions. While Hayfever and Osteoarthritis show significant Over-the-Counter (OTC) accessibility, complex conditions like Diabetes and Pneumonia are managed almost exclusively through regulated prescriptions.

Thanks

I hope you enjoyed this notebook please consider voting up, Good luck