In [20]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# make plots look a bit nicer
sns.set_theme(style="whitegrid")

df = pd.read_excel("travel_emails.xlsx")

# Preview first few rows
df.head()
```

Out[20]:

	first_name	last_name	company_name	email
0	NaN	NaN	atoai	arshdeepanand@gmail.com
1	NaN	NaN	atoai	milind@countrysideindia.com
2	NaN	NaN	atoai	info@junoonadventure.in
3	NaN	NaN	atoai	east_chapter@atoai.org
4	NaN	NaN	atoai	north_chapter@atoai.org

In [21]:

```
# Basic shape (total records) and column names
total_records = len(df)
columns = df.columns.tolist()
total_records, columns
```

Out[21]:

```
(1129, ['first_name', 'last_name', 'company_name', 'email'])
```

In [24]:

```
# Derive generic vs non-generic (enhanced rule including company/domain match)
import re

generic_prefixes = ('info','support','admin','hello')

def classify_generic(row):
    email = str(row['email']).strip()
    company = str(row['company_name']).strip()
    first = str(row['first_name']).strip()
    last = str(row['last_name']).strip()

    # Basic guards
    if '@' not in email:
        return 'non-generic'

    local = email.split('@')[0].lower()
    domain_root = email.split('@')[1].split('.')[0].lower()

    # Normalization helper: remove non-alphanumeric to compare fairly
    norm = lambda s: re.sub(r'[^a-z0-9]', '', s.lower())
    company_norm = norm(company)
    domain_norm = norm(domain_root)
    first_norm = norm(first)
```

```python
    last_norm = norm(last)

    # prefix-based generic
    prefix_generic = any(local.startswith(p) for p in generic_prefixes)

    # domain/company match
    # Match if equal OR one contained in the other
    company_domain_match = (
        company_norm and domain_norm and
        (company_norm == domain_norm or
         company_norm in domain_norm or
         domain_norm in company_norm)
    )

    # if local part looks like a personal address
    personal_like = (
        first_norm and last_norm and
        first_norm in local and
        last_norm in local
    )

    # Final decision logic
    if prefix_generic:
        return 'generic'
    if company_domain_match and not personal_like:
        # Treat functional/local names (e.g., projectzone@company.com) as generic
        return 'generic'
    return 'non-generic'

# Apply classification
email_type = df.apply(classify_generic, axis=1)

# Counts & percentages (same downstream usage as before)
email_type_counts = email_type.value_counts()
email_type_pct = (email_type_counts / len(df) * 100).round(2)
email_type_counts, email_type_pct
```

Out[24]:

```
(non-generic    961
 generic        168
 Name: count, dtype: int64,
 non-generic    85.12
 generic        14.88
 Name: count, dtype: float64)
```

In [26]:

```python
# Most frequent company names (top 10) - clean blanks/NaN
top_companies = (
    df['company_name']
      .astype(str)
      .str.strip()
      .replace({'': pd.NA, 'nan': pd.NA})
      .dropna()
      .value_counts()
      .head(10)
)
top_companies
```

Out[26]:

```
company_name
Tourism                                       458
Keralatourism                                 391
iato                                          158
Gujarattourism                                 48
atoai                                          43
india tourism development corporation          16
Exploreworldtourism                             4
Travellshop                                     3
Traveldreamz                                    2
Incredibleindia                                 2
Name: count, dtype: int64
```

In [11]:

```python
# Most frequent company names (exclude NaN)
top_companies = (
    df['company_name']
      .dropna()
      .str.strip()
      .replace('', pd.NA)
      .dropna()
      .value_counts()
      .head(10)
)
top_companies
```

Out[11]:

```
company_name
Tourism                                       458
Keralatourism                                 391
iato                                          158
Gujarattourism                                 48
atoai                                          43
india tourism development corporation          16
Exploreworldtourism                             4
Travellshop                                     3
Traveldreamz                                    2
Incredibleindia                                 2
Name: count, dtype: int64
```

In [27]:

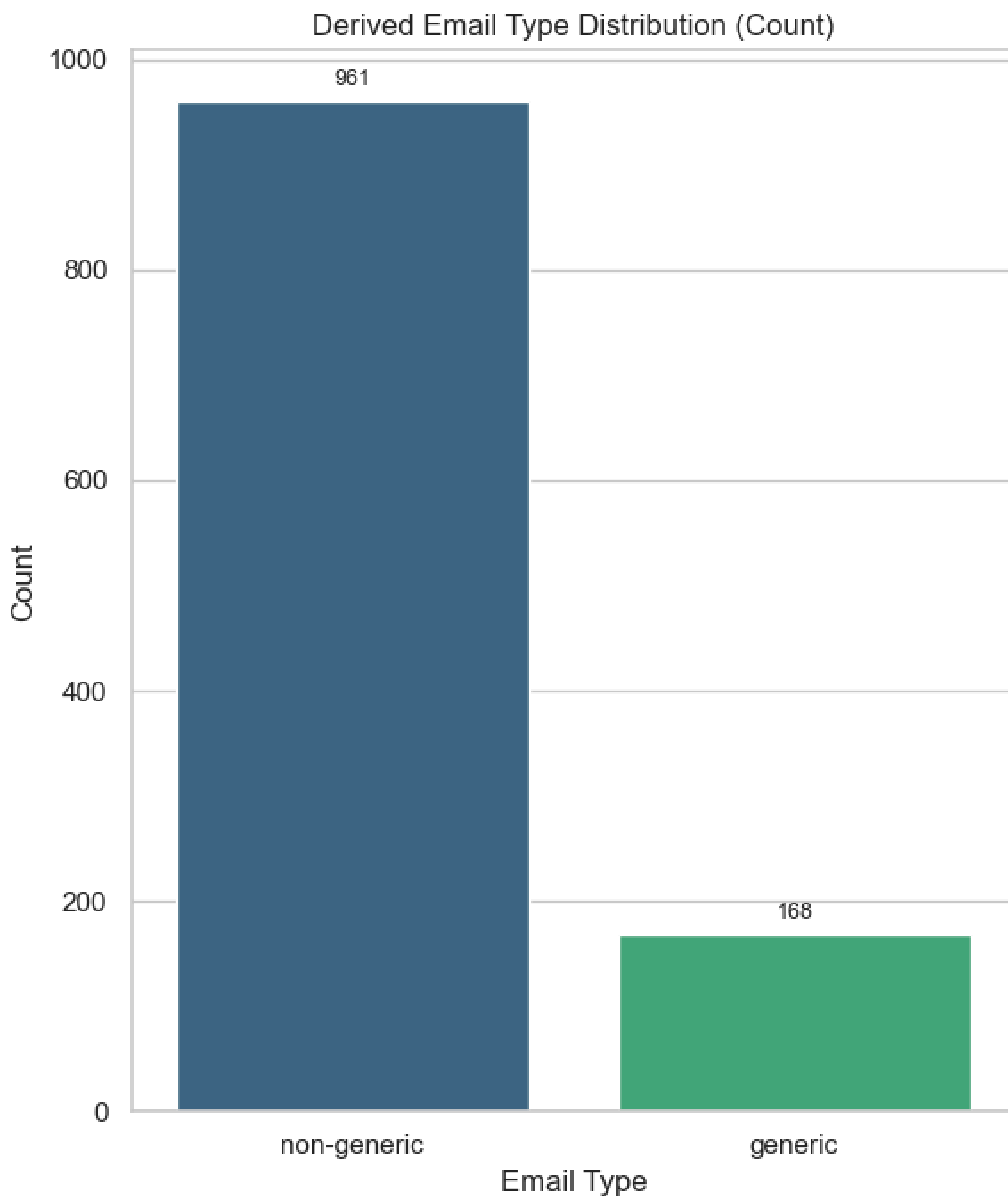
```python
# Missing value summary (only the four columns)
missing_counts = df.isna().sum()
missing_percent = (missing_counts / total_records * 100).round(2)
missing_summary = pd.DataFrame({
    'missing_count': missing_counts,
    'missing_percent': missing_percent
})
missing_summary
```

Out[27]:

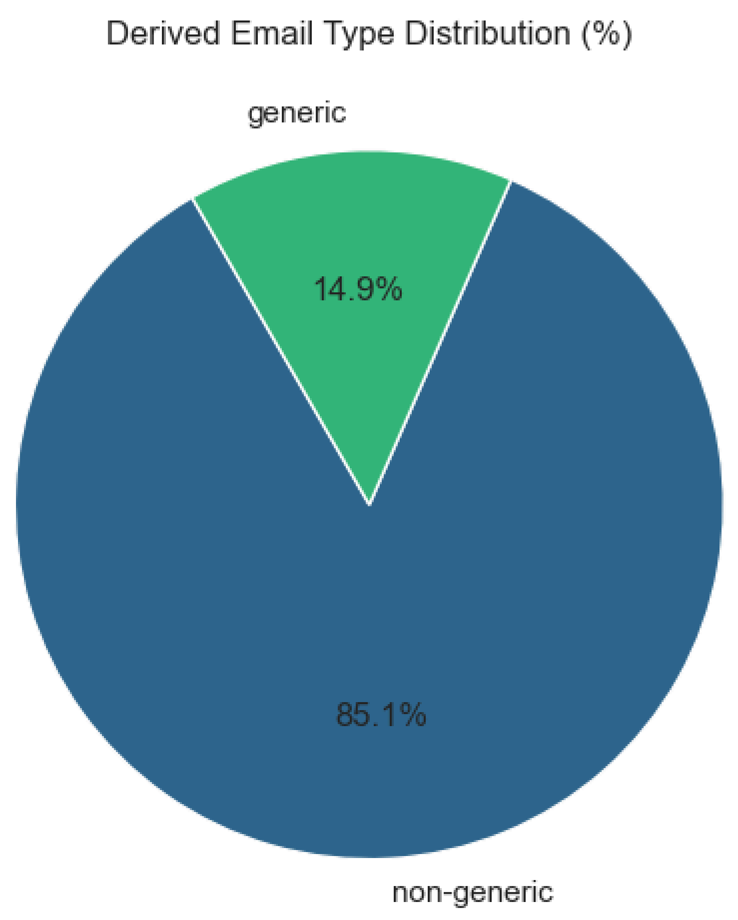
	missing_count	missing_percent
first_name	278	24.62
last_name	725	64.22
company_name	0	0.00
email	0	0.00

In [34]:

```
# Visualization 1: Bar chart of derived email_type counts
counts_df = email_type_counts.reset_index()
counts_df.columns = ['email_type','count']

plt.figure(figsize=(6,7))
sns.barplot(
    data=counts_df,
    x='email_type',
    y='count',
    hue='email_type',
    palette='viridis',

)
plt.title("Derived Email Type Distribution (Count)")
plt.xlabel("Email Type")
plt.ylabel("Count")

# Add numeric labels above bars
for i, row in counts_df.iterrows():
    plt.text(
        i,
        row['count'] + counts_df['count'].max()*0.01,  # slight vertical offset
        str(row['count']),
        ha='center',
        va='bottom',
        fontsize=9
    )

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



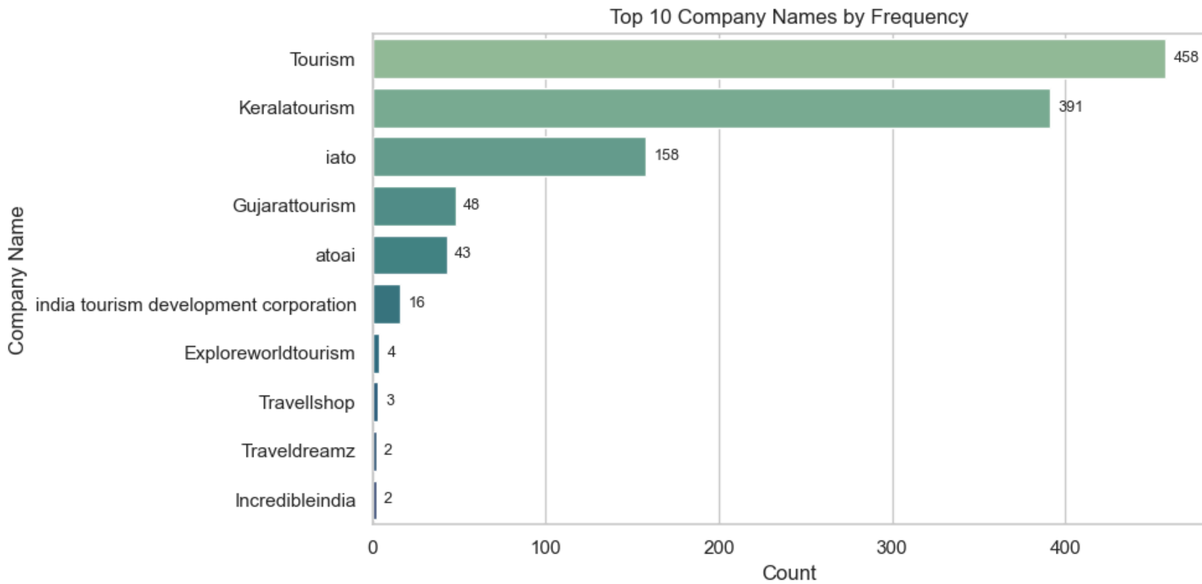
In [35]:
```
# Visualization 2: Pie chart (percentage share)
plt.figure(figsize=(5,5))
plt.pie(
    email_type_counts.values,
    labels=email_type_counts.index,
    autopct='%1.1f%%',
    startangle=120,
    colors=sns.color_palette("viridis", n_colors=len(email_type_counts))
)
plt.title("Derived Email Type Distribution (%)")
plt.tight_layout()
plt.show()
```



In [38]:

```
# Top 10 company frequency bar chart

top_companies_df = top_companies.reset_index()
top_companies_df.columns = ['company_name','count']

plt.figure(figsize=(10,5))
sns.barplot(
    data=top_companies_df,
    y='company_name',
    x='count',
    hue='company_name',
    palette='crest',
    dodge=False,
    legend=False
)
plt.title("Top 10 Company Names by Frequency")
plt.xlabel("Count")
plt.ylabel("Company Name")
for i, row in top_companies_df.iterrows():
    plt.text(
        row['count'] + top_companies_df['count'].max()*0.01,
        i,
        str(row['count']),
        va='center',
        fontsize=9
    )
```

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



In [42]:

```
# Compact summary dictionary
summary = {
    "total_records": total_records,
    "generic_count": int(email_type_counts.get('generic', 0)),
    "non_generic_count": int(email_type_counts.get('non-generic', 0))
}
summary["generic %"] = round(summary["generic_count"]/summary["total_records"]*100,
summary["non_generic %"] = round(summary["non_generic_count"]/summary["total_record
summary
```

Out[42]:

```
{'total_records': 1129,
 'generic_count': 168,
 'non_generic_count': 961,
 'generic %': 14.88,
 'non_generic %': 85.12}
```

In [45]:

```
Some Insights
1. Personalized (non-generic) emails dominate, signaling strong direct contact poten
tial.
2. Domain roots usually mirror company names data likely sourced from official corpo
rate domains.
3. Extra generics were found by matching company name to domain.
4. A few companies appear very frequently.
5. Data has alot of missing values in last_name column with 64.22%.
```