In [1]:
```
import pandas as pd
```

In [2]:
```
applicationdf = pd.read_csv(r"C:\Users\godis\Desktop\OneDrive - University of St
```

In [3]:
```
applicationdf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(41), object(16)
memory usage: 286.2+ MB
```

In [4]:
```
print(applicationdf.isnull().sum())
```

```
SK_ID_CURR                        0
TARGET                            0
NAME_CONTRACT_TYPE                0
CODE_GENDER                       0
FLAG_OWN_CAR                      0
                              ...
AMT_REQ_CREDIT_BUREAU_DAY     41519
AMT_REQ_CREDIT_BUREAU_WEEK    41519
AMT_REQ_CREDIT_BUREAU_MON     41519
AMT_REQ_CREDIT_BUREAU_QRT     41519
AMT_REQ_CREDIT_BUREAU_YEAR    41519
Length: 122, dtype: int64
```

In [5]:
```
applicationdf.head()
```

Out[5]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLA
0	100002	1	Cash loans	M	N	
1	100003	0	Cash loans	F	N	
2	100004	0	Revolving loans	M	Y	
3	100006	0	Cash loans	F	N	
4	100007	0	Cash loans	M	N	

5 rows × 122 columns

In [6]:
```
# data loaded in data frame
missing_percentage = applicationdf.isnull().sum() * 100 / len(applicationdf)

# Identifying columns where more than 50% of the data is missing
high_missing_cols = missing_percentage[missing_percentage > 50].sort_values(asce

# Storing the list of columns to drop
cols_to_drop = high_missing_cols.index.tolist()

# Dropping the columns
applicationdf.drop(columns=cols_to_drop, inplace=True)

#checking wether columns dropped or not
```

```
print("Columns Dropped (over 50% missing data):", cols_to_drop)
print(f"New DataFrame shape: {applicationdf.shape}")
```

```
Columns Dropped (over 50% missing data): ['COMMONAREA_AVG', 'COMMONAREA_MEDI', 'C
OMMONAREA_MODE', 'NONLIVINGAPARTMENTS_AVG', 'NONLIVINGAPARTMENTS_MODE', 'NONLIVIN
GAPARTMENTS_MEDI', 'FONDKAPREMONT_MODE', 'LIVINGAPARTMENTS_AVG', 'LIVINGAPARTMENT
S_MODE', 'LIVINGAPARTMENTS_MEDI', 'FLOORSMIN_MODE', 'FLOORSMIN_MEDI', 'FLOORSMIN_
AVG', 'YEARS_BUILD_MODE', 'YEARS_BUILD_MEDI', 'YEARS_BUILD_AVG', 'OWN_CAR_AGE',
'LANDAREA_MODE', 'LANDAREA_MEDI', 'LANDAREA_AVG', 'BASEMENTAREA_MODE', 'BASEMENTA
REA_AVG', 'BASEMENTAREA_MEDI', 'EXT_SOURCE_1', 'NONLIVINGAREA_MEDI', 'NONLIVINGAR
EA_AVG', 'NONLIVINGAREA_MODE', 'ELEVATORS_AVG', 'ELEVATORS_MODE', 'ELEVATORS_MED
I', 'WALLSMATERIAL_MODE', 'APARTMENTS_MEDI', 'APARTMENTS_AVG', 'APARTMENTS_MODE',
'ENTRANCES_AVG', 'ENTRANCES_MODE', 'ENTRANCES_MEDI', 'LIVINGAREA_MODE', 'LIVINGAR
EA_AVG', 'LIVINGAREA_MEDI', 'HOUSETYPE_MODE']
New DataFrame shape: (307511, 81)
```

In [7]:

```
applicationdf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Data columns (total 81 columns):
 #   Column                        Non-Null Count   Dtype  
---  ------                        --------------   -----  
 0   SK_ID_CURR                    307511 non-null  int64  
 1   TARGET                        307511 non-null  int64  
 2   NAME_CONTRACT_TYPE            307511 non-null  object 
 3   CODE_GENDER                   307511 non-null  object 
 4   FLAG_OWN_CAR                  307511 non-null  object 
 5   FLAG_OWN_REALTY               307511 non-null  object 
 6   CNT_CHILDREN                  307511 non-null  int64  
 7   AMT_INCOME_TOTAL              307511 non-null  float64
 8   AMT_CREDIT                    307511 non-null  float64
 9   AMT_ANNUITY                   307499 non-null  float64
 10  AMT_GOODS_PRICE               307233 non-null  float64
 11  NAME_TYPE_SUITE               306219 non-null  object 
 12  NAME_INCOME_TYPE              307511 non-null  object 
 13  NAME_EDUCATION_TYPE           307511 non-null  object 
 14  NAME_FAMILY_STATUS            307511 non-null  object 
 15  NAME_HOUSING_TYPE             307511 non-null  object 
 16  REGION_POPULATION_RELATIVE    307511 non-null  float64
 17  DAYS_BIRTH                    307511 non-null  int64  
 18  DAYS_EMPLOYED                 307511 non-null  int64  
 19  DAYS_REGISTRATION             307511 non-null  float64
 20  DAYS_ID_PUBLISH               307511 non-null  int64  
 21  FLAG_MOBIL                    307511 non-null  int64  
 22  FLAG_EMP_PHONE                307511 non-null  int64  
 23  FLAG_WORK_PHONE               307511 non-null  int64  
 24  FLAG_CONT_MOBILE              307511 non-null  int64  
 25  FLAG_PHONE                    307511 non-null  int64  
 26  FLAG_EMAIL                    307511 non-null  int64  
 27  OCCUPATION_TYPE               211120 non-null  object 
 28  CNT_FAM_MEMBERS               307509 non-null  float64
 29  REGION_RATING_CLIENT          307511 non-null  int64  
 30  REGION_RATING_CLIENT_W_CITY   307511 non-null  int64  
 31  WEEKDAY_APPR_PROCESS_START    307511 non-null  object 
 32  HOUR_APPR_PROCESS_START       307511 non-null  int64  
 33  REG_REGION_NOT_LIVE_REGION    307511 non-null  int64  
 34  REG_REGION_NOT_WORK_REGION    307511 non-null  int64  
 35  LIVE_REGION_NOT_WORK_REGION   307511 non-null  int64  
 36  REG_CITY_NOT_LIVE_CITY        307511 non-null  int64  
 37  REG_CITY_NOT_WORK_CITY        307511 non-null  int64  
 38  LIVE_CITY_NOT_WORK_CITY       307511 non-null  int64  
 39  ORGANIZATION_TYPE             307511 non-null  object 
 40  EXT_SOURCE_2                  306851 non-null  float64
 41  EXT_SOURCE_3                  246546 non-null  float64
 42  YEARS_BEGINEXPLUATATION_AVG   157504 non-null  float64
 43  FLOORSMAX_AVG                 154491 non-null  float64
 44  YEARS_BEGINEXPLUATATION_MODE  157504 non-null  float64
 45  FLOORSMAX_MODE                154491 non-null  float64
 46  YEARS_BEGINEXPLUATATION_MEDI  157504 non-null  float64
 47  FLOORSMAX_MEDI                154491 non-null  float64
 48  TOTALAREA_MODE                159080 non-null  float64
 49  EMERGENCYSTATE_MODE           161756 non-null  object 
 50  OBS_30_CNT_SOCIAL_CIRCLE      306490 non-null  float64
 51  DEF_30_CNT_SOCIAL_CIRCLE      306490 non-null  float64
 52  OBS_60_CNT_SOCIAL_CIRCLE      306490 non-null  float64
 53  DEF_60_CNT_SOCIAL_CIRCLE      306490 non-null  float64
 54  DAYS_LAST_PHONE_CHANGE        307510 non-null  float64
```

```
 55   FLAG_DOCUMENT_2              307511 non-null  int64
 56   FLAG_DOCUMENT_3              307511 non-null  int64
 57   FLAG_DOCUMENT_4              307511 non-null  int64
 58   FLAG_DOCUMENT_5              307511 non-null  int64
 59   FLAG_DOCUMENT_6              307511 non-null  int64
 60   FLAG_DOCUMENT_7              307511 non-null  int64
 61   FLAG_DOCUMENT_8              307511 non-null  int64
 62   FLAG_DOCUMENT_9              307511 non-null  int64
 63   FLAG_DOCUMENT_10             307511 non-null  int64
 64   FLAG_DOCUMENT_11             307511 non-null  int64
 65   FLAG_DOCUMENT_12             307511 non-null  int64
 66   FLAG_DOCUMENT_13             307511 non-null  int64
 67   FLAG_DOCUMENT_14             307511 non-null  int64
 68   FLAG_DOCUMENT_15             307511 non-null  int64
 69   FLAG_DOCUMENT_16             307511 non-null  int64
 70   FLAG_DOCUMENT_17             307511 non-null  int64
 71   FLAG_DOCUMENT_18             307511 non-null  int64
 72   FLAG_DOCUMENT_19             307511 non-null  int64
 73   FLAG_DOCUMENT_20             307511 non-null  int64
 74   FLAG_DOCUMENT_21             307511 non-null  int64
 75   AMT_REQ_CREDIT_BUREAU_HOUR   265992 non-null  float64
 76   AMT_REQ_CREDIT_BUREAU_DAY    265992 non-null  float64
 77   AMT_REQ_CREDIT_BUREAU_WEEK   265992 non-null  float64
 78   AMT_REQ_CREDIT_BUREAU_MON    265992 non-null  float64
 79   AMT_REQ_CREDIT_BUREAU_QRT    265992 non-null  float64
 80   AMT_REQ_CREDIT_BUREAU_YEAR   265992 non-null  float64
dtypes: float64(27), int64(41), object(13)
memory usage: 190.0+ MB
```

In [8]:

```python
# Finding all remaining columns that are numerical (float or int) AND have missi
# Re-running the original check on the updated DataFrame
numerical_missing_cols = applicationdf.select_dtypes(include=['float64', 'int64'

print("--- Numerical Columns to Impute ---")
print(numerical_missing_cols)
print("-----------------------------------")

for col in numerical_missing_cols:
    median_val = applicationdf[col].median()
    applicationdf[col].fillna(median_val, inplace=True)
    print(f"Imputed numerical column '{col}' with median: {median_val}")

# Verifying all numerical missing values are resolved or not
print("\nVerification: Remaining missing values in numerical columns:")
print(applicationdf[numerical_missing_cols].isnull().sum().sum())
```

```
--- Numerical Columns to Impute ---
['AMT_ANNUITY', 'AMT_GOODS_PRICE', 'CNT_FAM_MEMBERS', 'EXT_SOURCE_2', 'EXT_SOURCE
_3', 'YEARS_BEGINEXPLUATATION_AVG', 'FLOORSMAX_AVG', 'YEARS_BEGINEXPLUATATION_MOD
E', 'FLOORSMAX_MODE', 'YEARS_BEGINEXPLUATATION_MEDI', 'FLOORSMAX_MEDI', 'TOTALARE
A_MODE', 'OBS_30_CNT_SOCIAL_CIRCLE', 'DEF_30_CNT_SOCIAL_CIRCLE', 'OBS_60_CNT_SOCI
AL_CIRCLE', 'DEF_60_CNT_SOCIAL_CIRCLE', 'DAYS_LAST_PHONE_CHANGE', 'AMT_REQ_CREDIT
_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK', 'AMT_RE
Q_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR']
-----------------------------------
Imputed numerical column 'AMT_ANNUITY' with median: 24903.0
Imputed numerical column 'AMT_GOODS_PRICE' with median: 450000.0
Imputed numerical column 'CNT_FAM_MEMBERS' with median: 2.0
Imputed numerical column 'EXT_SOURCE_2' with median: 0.5659614260608526
Imputed numerical column 'EXT_SOURCE_3' with median: 0.5352762504724826
Imputed numerical column 'YEARS_BEGINEXPLUATATION_AVG' with median: 0.9816
Imputed numerical column 'FLOORSMAX_AVG' with median: 0.1667
Imputed numerical column 'YEARS_BEGINEXPLUATATION_MODE' with median: 0.9816
Imputed numerical column 'FLOORSMAX_MODE' with median: 0.1667
Imputed numerical column 'YEARS_BEGINEXPLUATATION_MEDI' with median: 0.9816
Imputed numerical column 'FLOORSMAX_MEDI' with median: 0.1667
Imputed numerical column 'TOTALAREA_MODE' with median: 0.0688
Imputed numerical column 'OBS_30_CNT_SOCIAL_CIRCLE' with median: 0.0
Imputed numerical column 'DEF_30_CNT_SOCIAL_CIRCLE' with median: 0.0
Imputed numerical column 'OBS_60_CNT_SOCIAL_CIRCLE' with median: 0.0
Imputed numerical column 'DEF_60_CNT_SOCIAL_CIRCLE' with median: 0.0
Imputed numerical column 'DAYS_LAST_PHONE_CHANGE' with median: -757.0
Imputed numerical column 'AMT_REQ_CREDIT_BUREAU_HOUR' with median: 0.0
Imputed numerical column 'AMT_REQ_CREDIT_BUREAU_DAY' with median: 0.0
Imputed numerical column 'AMT_REQ_CREDIT_BUREAU_WEEK' with median: 0.0
Imputed numerical column 'AMT_REQ_CREDIT_BUREAU_MON' with median: 0.0
Imputed numerical column 'AMT_REQ_CREDIT_BUREAU_QRT' with median: 0.0
Imputed numerical column 'AMT_REQ_CREDIT_BUREAU_YEAR' with median: 1.0

Verification: Remaining missing values in numerical columns:
0
```

```
C:\Users\godis\AppData\Local\Temp\ipykernel_13044\1207936534.py:11: FutureWarnin
g: A value is trying to be set on a copy of a DataFrame or Series through chained
assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work becau
se the intermediate object on which we are setting values always behaves as a cop
y.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.meth
od({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to pe
rform the operation inplace on the original object.


  applicationdf[col].fillna(median_val, inplace=True)
```

In [9]:
```
# Identifying all remaining categorical columns with missing values
categorical_missing_cols = applicationdf.select_dtypes(include=['object']).colum

print("\n--- Categorical Columns to Impute ---")
print(categorical_missing_cols)
print("-----------------------------------")

for col in categorical_missing_cols:
    # Filling missing values with 'Missing'
    applicationdf[col].fillna('Missing', inplace=True)
    print(f"Imputed categorical column '{col}' with 'Missing'")
```

```
# Verifying that all missing values in the entire DataFrame are resolved
print(f"\nTotal remaining missing values in DataFrame: {applicationdf.isnull().s
```

```
--- Categorical Columns to Impute ---
['NAME_TYPE_SUITE', 'OCCUPATION_TYPE', 'EMERGENCYSTATE_MODE']
-----------------------------------
Imputed categorical column 'NAME_TYPE_SUITE' with 'Missing'
Imputed categorical column 'OCCUPATION_TYPE' with 'Missing'
Imputed categorical column 'EMERGENCYSTATE_MODE' with 'Missing'

Total remaining missing values in DataFrame: 0
```

```
C:\Users\godis\AppData\Local\Temp\ipykernel_13044\1702331462.py:10: FutureWarnin
g: A value is trying to be set on a copy of a DataFrame or Series through chained
assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work becau
se the intermediate object on which we are setting values always behaves as a cop
y.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.meth
od({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to pe
rform the operation inplace on the original object.


  applicationdf[col].fillna('Missing', inplace=True)
```

In [10]:

```
# Identifying all the object columns that need encoding
categorical_cols_to_encode = applicationdf.select_dtypes(include=['object']).col

# Applying One-Hot Encoding and dropping the original categorical columns
applicationdf = pd.get_dummies(applicationdf, columns=categorical_cols_to_encode

# Verifying the final shape
print(f"\nFinal DataFrame shape after encoding: {applicationdf.shape}")
print(f"Number of columns after encoding: {applicationdf.shape[1]}")


print("Sample Encoded Columns (First 5 Rows):")
print(applicationdf.filter(regex='_M$|_F$|_Cash_loans$|_Missing$').head())
```

```
Final DataFrame shape after encoding: (307511, 184)
Number of columns after encoding: 184
Sample Encoded Columns (First 5 Rows):
   CODE_GENDER_M  NAME_TYPE_SUITE_Missing  OCCUPATION_TYPE_Missing
0           True                    False                    False
1          False                    False                    False
2           True                    False                    False
3          False                    False                    False
4           True                    False                    False
```

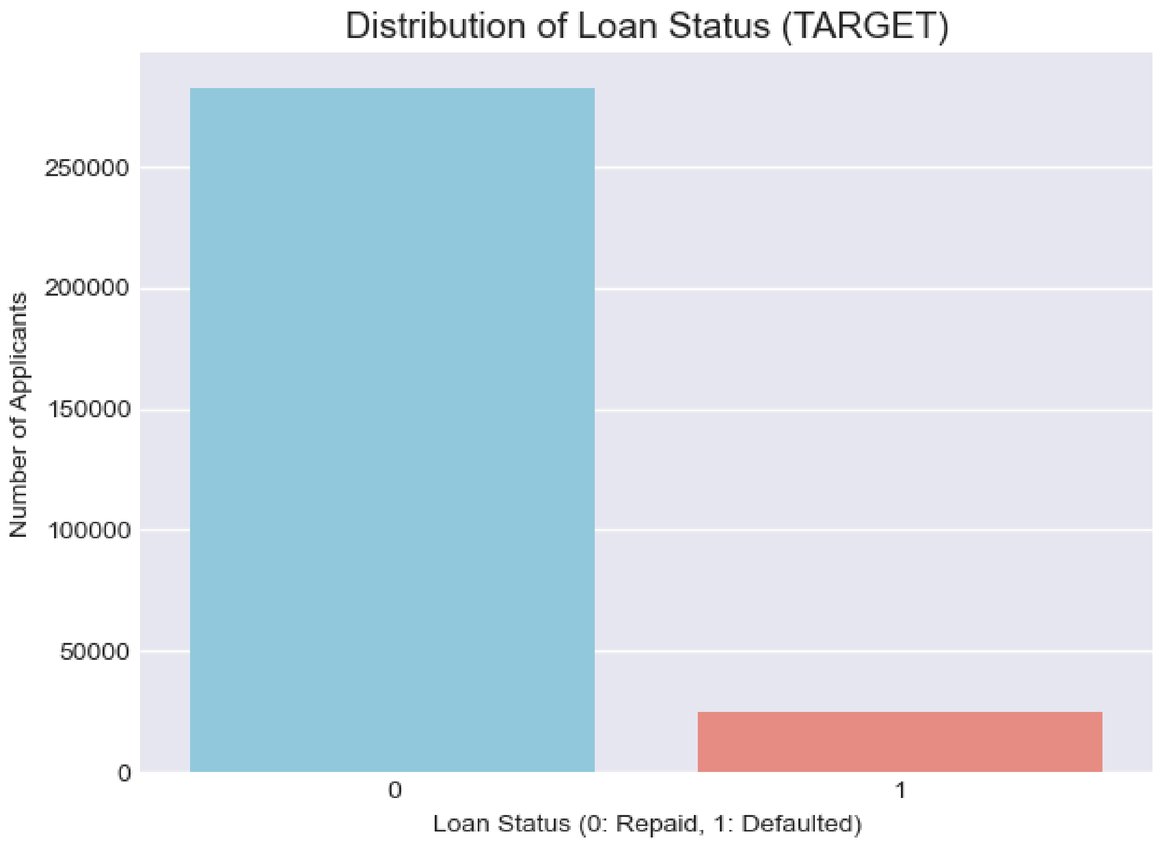
In [11]:

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

# Setting a style for better visualization
plt.style.use("seaborn-v0_8-darkgrid")

# 1. Checking the distribution of the TARGET variable
target_counts = applicationdf['TARGET'].value_counts()
target_proportions = target_counts / len(applicationdf) * 100
```

```
print("Target Variable Distribution:")
print(target_counts)
print(f"Proportion of Non-Defaulters (0): {target_proportions.iloc[0]:.2f}%")
print(f"Proportion of Defaulters (1): {target_proportions.iloc[1]:.2f}%")

# 2. Visualizing the distribution using a Bar Chart
plt.figure(figsize=(7, 5))
sns.barplot(x=target_counts.index, y=target_counts.values, palette=['skyblue', '
plt.title('Distribution of Loan Status (TARGET)', fontsize=14)
plt.xlabel('Loan Status (0: Repaid, 1: Defaulted)')
plt.ylabel('Number of Applicants')
plt.xticks([0, 1])
plt.show()
```

```
Target Variable Distribution:
TARGET
0    282686
1     24825
Name: count, dtype: int64
Proportion of Non-Defaulters (0): 91.93%
Proportion of Defaulters (1): 8.07%
```

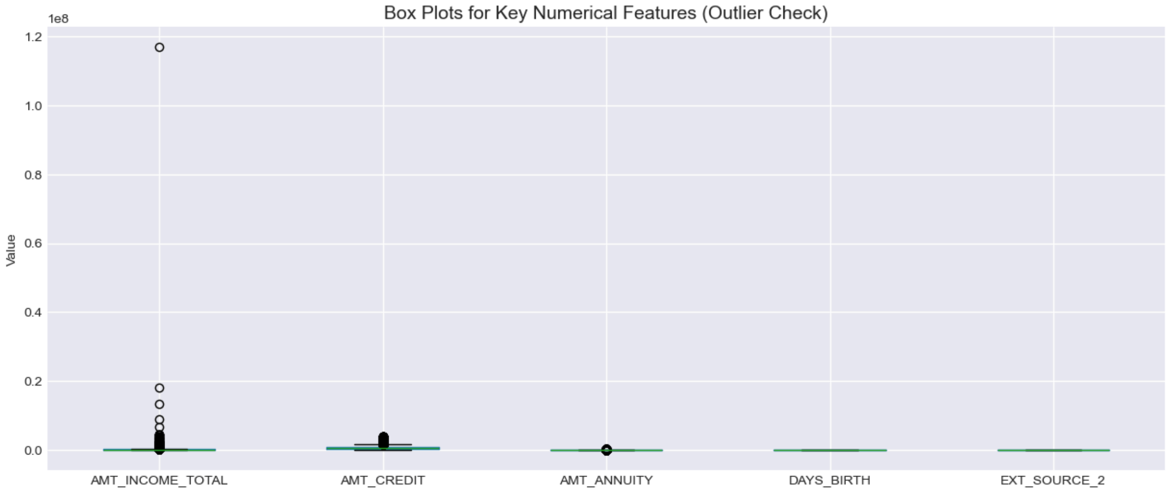
```
C:\Users\godis\AppData\Local\Temp\ipykernel_13044\4138747666.py:18: FutureWarnin
g: 

Passing `palette` without assigning `hue` is deprecated and will be removed in v
0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effe
ct.

  sns.barplot(x=target_counts.index, y=target_counts.values, palette=['skyblue', 
'salmon'])
```

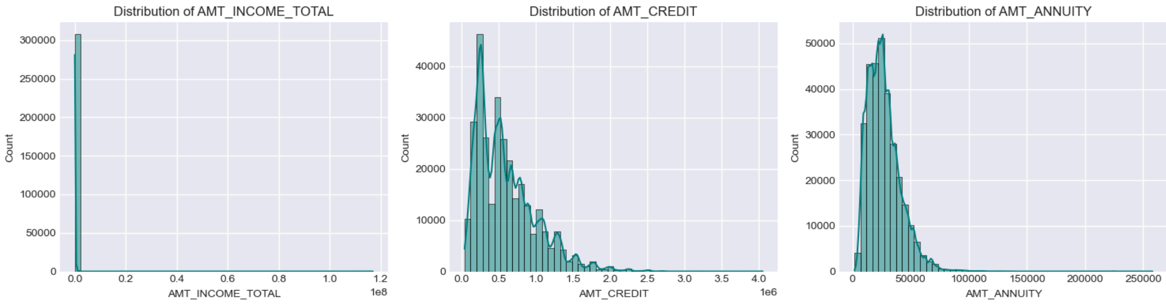


In [12]:
```
# Selecting the most critical financial and demographic features
key_numeric_features = ['AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY', 'DAYS_B
```

```
# 1. Descriptive Statistics Table
print("\n--- Descriptive Statistics Table ---")
print(applicationdf[key_numeric_features].describe())

# 2. Box Plots
plt.figure(figsize=(15, 6))
applicationdf[key_numeric_features].boxplot()
plt.title('Box Plots for Key Numerical Features (Outlier Check)', fontsize=14)
plt.ylabel('Value')
plt.show()

# 3. Histograms
plt.figure(figsize=(15, 4))
for i, col in enumerate(key_numeric_features[:3]): # Focusing on the monetary co
    plt.subplot(1, 3, i + 1)
    sns.histplot(applicationdf[col], kde=True, bins=50, color='teal')
    plt.title(f'Distribution of {col}', fontsize=12)
    plt.xlabel(col)
plt.tight_layout()
plt.show()
```

```
--- Descriptive Statistics Table ---
       AMT_INCOME_TOTAL    AMT_CREDIT    AMT_ANNUITY     DAYS_BIRTH  \
count      3.075110e+05  3.075110e+05  307511.000000  307511.000000
mean       1.687979e+05  5.990260e+05   27108.487841  -16036.995067
std        2.371231e+05  4.024908e+05   14493.461065    4363.988632
min        2.565000e+04  4.500000e+04    1615.500000  -25229.000000
25%        1.125000e+05  2.700000e+05   16524.000000  -19682.000000
50%        1.471500e+05  5.135310e+05   24903.000000  -15750.000000
75%        2.025000e+05  8.086500e+05   34596.000000  -12413.000000
max        1.170000e+08  4.050000e+06  258025.500000   -7489.000000

       EXT_SOURCE_2
count  3.075110e+05
mean   5.145034e-01
std    1.908699e-01
min    8.173617e-08
25%    3.929737e-01
50%    5.659614e-01
75%    6.634218e-01
max    8.549997e-01
```

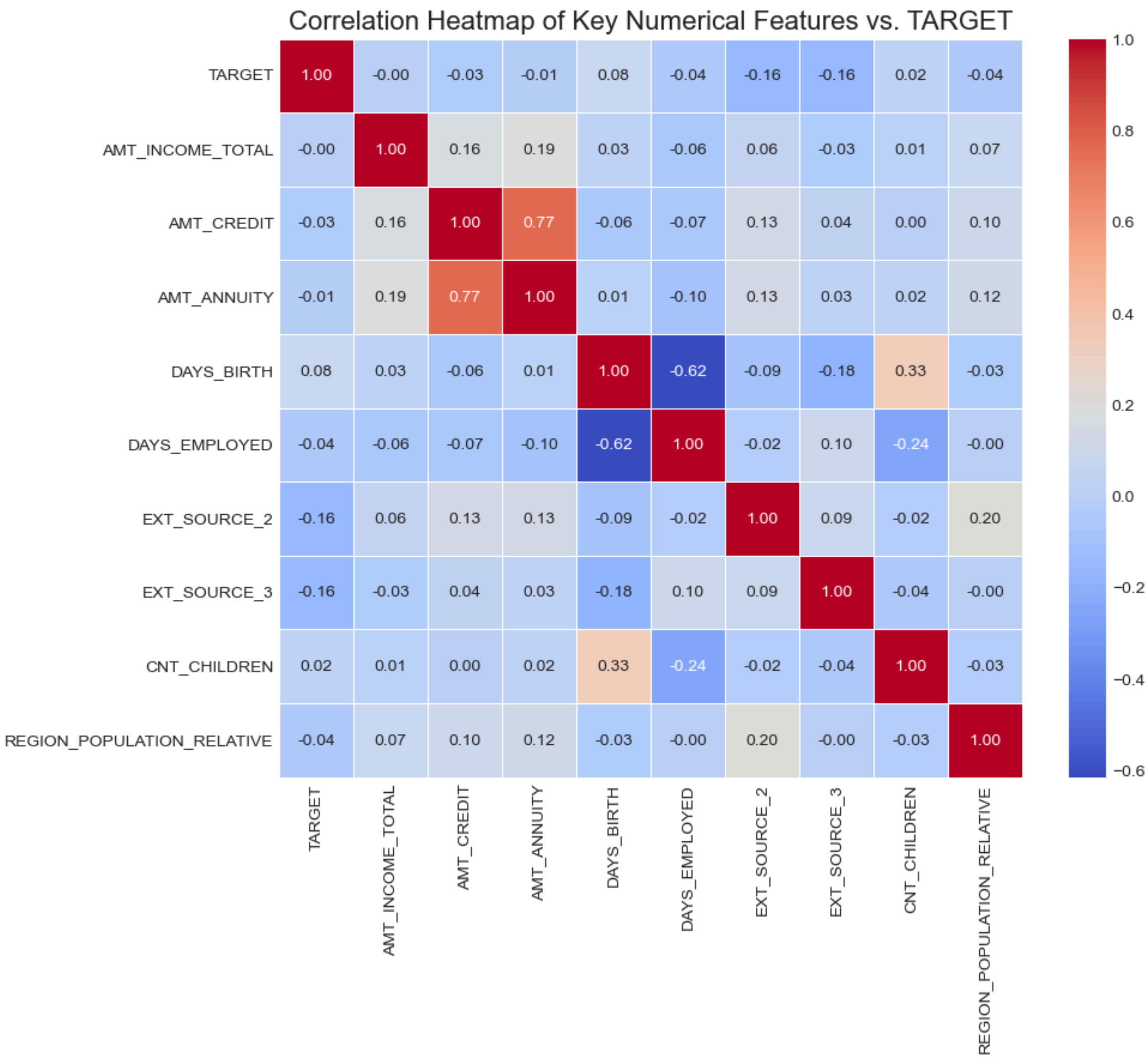




In [13]:
```python
# Assuming our clean DataFrame is named 'df'
numeric_corr_cols = ['TARGET', 'AMT_INCOME_TOTAL', 'AMT_CREDIT', 'AMT_ANNUITY',
                     'DAYS_BIRTH', 'DAYS_EMPLOYED', 'EXT_SOURCE_2', 'EXT_SOURCE_
                     'CNT_CHILDREN', 'REGION_POPULATION_RELATIVE']

correlation_matrix = applicationdf[numeric_corr_cols].corr()

# Printing the table
print("\n--- Correlation Matrix (for identifying top predictors) ---")
print(correlation_matrix.to_string())

# Visualizing the correlation matrix as a heatmap
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix,
            annot=True,
            cmap='coolwarm',
            fmt=".2f",
            linewidths=.5)
plt.title('Correlation Heatmap of Key Numerical Features vs. TARGET', fontsize=1
plt.show()
```

--- Correlation Matrix (for identifying top predictors) ---

	TARGET	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	DAYS_BIRTH	DAYS_EMPLOYED	EXT_SOURCE_2	EXT_SOURCE_3	CNT_CHILDREN	REGION_POPULATION_RELATIVE
TARGET	1.000000	-0.003982	-0.030369	-0.012815	0.078239	-0.044932	-0.160295	-0.155892	0.019187	-0.037227
AMT_INCOME_TOTAL	-0.003982	1.000000	0.156870	0.191657	0.027261	-0.064223	0.060855	-0.030737	0.012882	0.074796
AMT_CREDIT	-0.030369	0.156870	1.000000	0.770127	-0.055436	-0.066838	0.130930	0.036640	0.002145	0.099738
AMT_ANNUITY	-0.012815	0.191657	0.770127	1.000000	0.009443	-0.104329	0.125509	0.026738	0.021377	0.118418
DAYS_BIRTH	0.078239	0.027261	-0.055436	0.009443	1.000000	-0.615864	-0.091947	-0.178527	0.330938	-0.029582
DAYS_EMPLOYED	-0.044932	-0.064223	-0.066838	-0.104329	-0.615864	1.000000	-0.020652	0.101525	-0.239818	-0.003980
EXT_SOURCE_2	-0.160295	0.060855	0.130930	0.125509	-0.091947	-0.020652	1.000000	0.094147	-0.017990	0.198725
EXT_SOURCE_3	-0.155892	-0.030737	0.036640	0.026738	-0.178527	0.101525	0.094147	1.000000	-0.039543	-0.004507
CNT_CHILDREN	0.019187	0.012882	0.002145	0.021377	0.330938	-0.239818	-0.017990	-0.039543	1.000000	-0.025573
REGION_POPULATION_RELATIVE	-0.037227	0.074796	0.099738	0.118418	-0.029582	-0.003980	0.198725	-0.004507	-0.025573	1.000000



In [14]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA # Using PCA to verify clustering in 2D spa

# 1. Selecting key numerical features for clustering (excluding TARGET)
clustering_features = ['AMT_INCOME_TOTAL', 'AMT_CREDIT', 'EXT_SOURCE_2', 'EXT_SC
X_cluster = applicationdf[clustering_features]

# 2. Scaling the data (StandardScaler ensures mean=0 and std=1)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_cluster)
print("Data scaled successfully.")

# 3. Using PCA to reduce dimensions for visualization purposes (2D plot is bette
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)
print(f"PCA reduced data shape: {X_pca.shape}")
```

```
Data scaled successfully.
PCA reduced data shape: (307511, 2)
```

In [15]:
```
# Unsupervised Analysis
from sklearn.cluster import KMeans

# 1. Defining the clustering model (K=3)
kmeans = KMeans(n_clusters=3, random_state=42, n_init=10)

# 2. Fitting the model to the scaled data
```

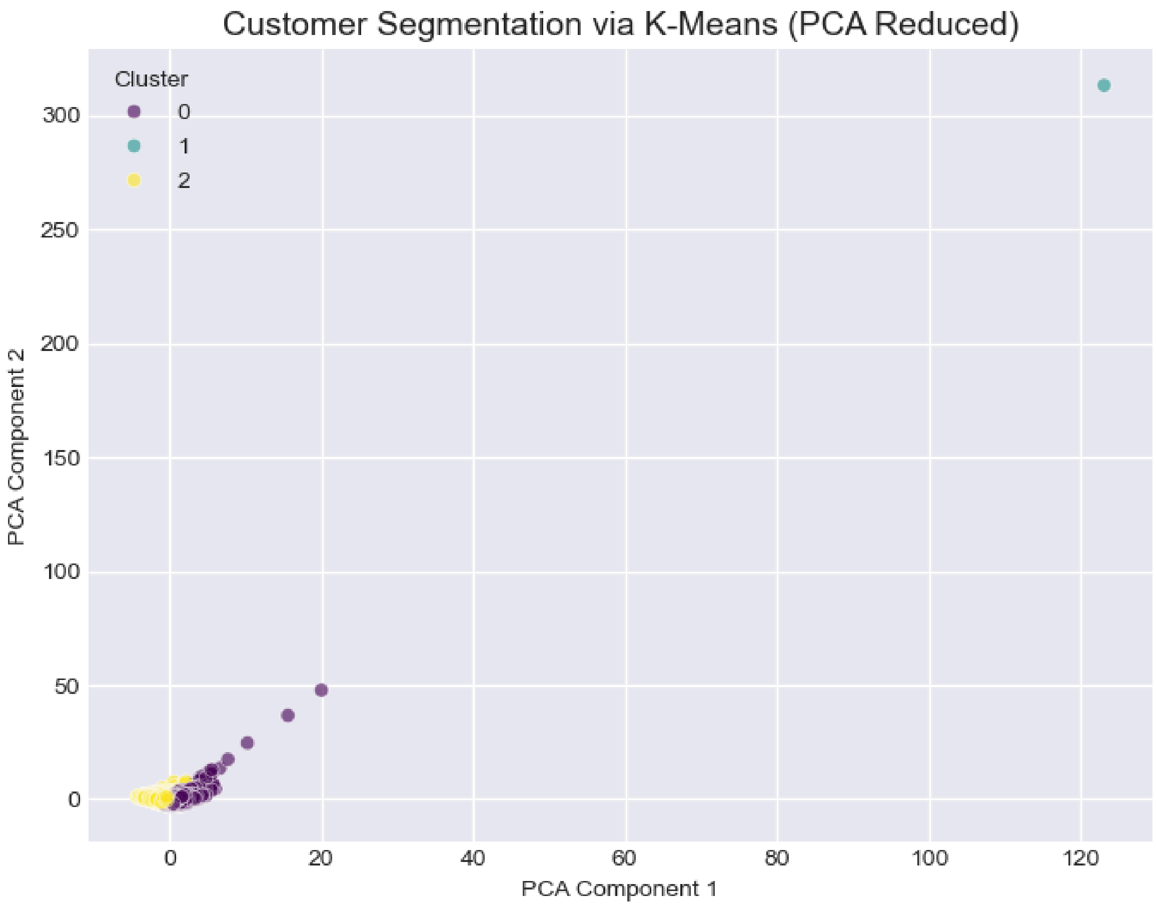
```
kmeans.fit(X_scaled)

# 3. Adding the cluster labels back to the main DataFrame
applicationdf['Cluster'] = kmeans.labels_

print("K-Means clustering completed with 3 clusters.")

# 4. Analyzing the size of each cluster
print("\nCluster Sizes:")
print(applicationdf['Cluster'].value_counts().sort_index())
```

```
K-Means clustering completed with 3 clusters.

Cluster Sizes:
Cluster
0    167683
1         1
2    139827
Name: count, dtype: int64
```

In [16]:

```
# 1. Analyzing the mean features for each cluster to interpret the groups
cluster_profiles = applicationdf.groupby('Cluster')[clustering_features + ['TARG
print("\n--- Cluster Profiles (Mean Feature Values) ---")
print(cluster_profiles)

# 2. Visualizing the Clusters in 2D Space (using PCA)
plt.figure(figsize=(8, 6))
sns.scatterplot(x=X_pca[:, 0], y=X_pca[:, 1], hue=applicationdf['Cluster'], pale
plt.title('Customer Segmentation via K-Means (PCA Reduced)', fontsize=14)
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.show()
```

```
--- Cluster Profiles (Mean Feature Values) ---
         AMT_INCOME_TOTAL     AMT_CREDIT  EXT_SOURCE_2  EXT_SOURCE_3  \
Cluster
0            1.760407e+05  710459.315941      0.582783      0.591805
1            1.170000e+08  562491.000000      0.113161      0.145543
2            1.592767e+05  465393.466423      0.432624      0.424425

           DAYS_BIRTH    TARGET
Cluster
0       -18496.962143  0.044125
1       -12615.000000  1.000000
2       -13086.983716  0.124618
```



In [17]:
```
# Supervised Analysis

from sklearn.model_selection import train_test_split

# Dropping the SK_ID_CURR (identifier) and the temporary 'Cluster' column before
X = applicationdf.drop(['SK_ID_CURR', 'TARGET', 'Cluster'], axis=1)
Y = applicationdf['TARGET']

# Spliting the data into training (70%) and testing (30%) sets
X_train, X_test, Y_train, Y_test = train_test_split(
    X, Y, test_size=0.3, random_state=42
)

print(f"Data split complete: Train shape = {X_train.shape}, Test shape = {X_test
```

```
Data split complete: Train shape = (215257, 182), Test shape = (92254, 182)
```

In [18]:
```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
import warnings

# Suppressing convergence warnings for cleaner output
warnings.filterwarnings('ignore')

# 1. Defining the model
model = LogisticRegression(solver='liblinear', random_state=42)

# 2. Training the model
model.fit(X_train, Y_train)

# 3. Predicting on the test set
Y_predicted = model.predict(X_test)
```

```python
# 4. Evaluating the model (Metrics for the report)
print("\n--- Logistic Regression Model Performance ---")
print("Classification Report:")
print(metrics.classification_report(Y_test, Y_predicted))

print("\nConfusion Matrix:")
print(metrics.confusion_matrix(Y_test, Y_predicted))

# 5. Calculating Accuracy
accuracy = metrics.accuracy_score(Y_test, Y_predicted)
print(f"\nOverall Accuracy: {accuracy:.4f}")
```

```
--- Logistic Regression Model Performance ---
Classification Report:
              precision    recall  f1-score   support

           0       0.92      1.00      0.96     84841
           1       0.00      0.00      0.00      7413

    accuracy                           0.92     92254
   macro avg       0.46      0.50      0.48     92254
weighted avg       0.85      0.92      0.88     92254


Confusion Matrix:
[[84840     1]
 [ 7413     0]]

Overall Accuracy: 0.9196
```

In [ ]:

In [ ]: