

FMCG Warehouse: Optimizing Amazon's Distribution Efficiency

Background:

You are a data analyst at Amazon, which has an extensive network of warehouses across various regions. The company is facing challenges in ensuring efficient warehouse operations, resulting in frequent stockouts, delays in deliveries, and increased operational costs. The management has tasked you with analyzing the data from these warehouses to identify key issues and provide actionable insights to enhance warehouse efficiency.

Problem Statement

Problem Statement: Amazon is experiencing inefficiencies in its warehouse operations. These inefficiencies are affecting the supply chain, leading to stockouts, delivery delays, and increased costs. Your task is to analyze warehouse data to uncover the root causes of these issues and propose data-driven solutions to optimize warehouse performance.

Importing Libraries

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

df = pd.read_csv("/content/FMCG_data.csv") #Loading the dataset
df.head()
```

↗

	Ware_house_ID	WH_Manager_ID	Location_type	WH_capacity_size	zone	WH_regional_zone	num_refill_req_13m	transport_issue_11y
0	WH_100000	EID_50000	Urban	Small	West	Zone 6	3	1
1	WH_100001	EID_50001	Rural	Large	North	Zone 5	0	0
2	WH_100002	EID_50002	Rural	Mid	South	Zone 2	1	0
3	WH_100003	EID_50003	Rural	Mid	North	Zone 3	7	4
4	WH_100004	EID_50004	Rural	Large	North	Zone 5	3	1

5 rows × 24 columns

```
df.isnull().sum() #checking for null values
```

↗

Ware_house_ID	0
WH_Manager_ID	0
Location_type	0
WH_capacity_size	0
zone	0
WH_regional_zone	0
num_refill_req_13m	0
transport_issue_11y	0
Competitor_in_mkt	0
retail_shop_num	0
wh_owner_type	0
distributor_num	0
flood_impacted	0
flood_proof	0
electric_supply	0
dist_from_hub	0
workers_num	990
wh_est_year	11881
storage_issue_reported_13m	0
temp_reg_mach	0
approved_wh_govt_certificate	908
wh_breakdown_13m	0
govt_check_13m	0
product_wg_ton	0
dtype: int64	

```
df.info() #checking for data types
```

↗

<class 'pandas.core.frame.DataFrame'>			
RangeIndex: 25000 entries, 0 to 24999			
Data columns (total 24 columns):			
#	Column	Non-Null Count	Dtype
---	-----	-----	----
0	Ware_house_ID	25000 non-null	object

```

1  WH_Manager_ID          25000 non-null object
2  Location_type          25000 non-null object
3  WH_capacity_size       25000 non-null object
4  zone                   25000 non-null object
5  WH_regional_zone       25000 non-null object
6  num_refill_req_l3m     25000 non-null int64
7  transport_issue_l1y    25000 non-null int64
8  Competitor_in_mkt      25000 non-null int64
9  retail_shop_num        25000 non-null int64
10 wh_owner_type          25000 non-null object
11 distributor_num        25000 non-null int64
12 flood_impacted         25000 non-null int64
13 flood_proof            25000 non-null int64
14 electric_supply        25000 non-null int64
15 dist_from_hub          25000 non-null int64
16 workers_num            24010 non-null float64
17 wh_est_year            13119 non-null float64
18 storage_issue_reported_l3m 25000 non-null int64
19 temp_reg_mach          25000 non-null int64
20 approved_wh_govt_certificate 24092 non-null object
21 wh_breakdown_l3m       25000 non-null int64
22 govt_check_l3m         25000 non-null int64
23 product_wg_ton         25000 non-null int64
dtypes: float64(2), int64(14), object(8)
memory usage: 4.6+ MB

```

```
df.shape #checking for number of rows and columns
```

```
(25000, 24)
```

```
df.columns #checking for columns
```

```

Index(['Ware_house_ID', 'WH_Manager_ID', 'Location_type', 'WH_capacity_size',
      'zone', 'WH_regional_zone', 'num_refill_req_l3m', 'transport_issue_l1y',
      'Competitor_in_mkt', 'retail_shop_num', 'wh_owner_type',
      'distributor_num', 'flood_impacted', 'flood_proof', 'electric_supply',
      'dist_from_hub', 'workers_num', 'wh_est_year',
      'storage_issue_reported_l3m', 'temp_reg_mach',
      'approved_wh_govt_certificate', 'wh_breakdown_l3m', 'govt_check_l3m',
      'product_wg_ton'],
      dtype='object')

```

▼ Data Analysis

Q1-What is the average capacity size of the warehouses?

```
cap_warehouse = df.groupby('WH_capacity_size')['Ware_house_ID'].nunique()
cap_warehouse
```

```

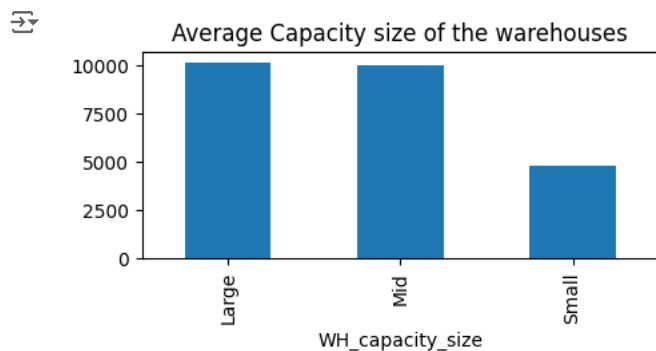
WH_capacity_size
Large      10169
Mid        10020
Small       4811
Name: Ware_house_ID, dtype: int64

```

```

cap_warehouse.plot(kind='bar', figsize=(5,2))
plt.title('Average Capacity size of the warehouses')
plt.show()

```



Q2- How many warehouses are located in urban areas versus rural areas?

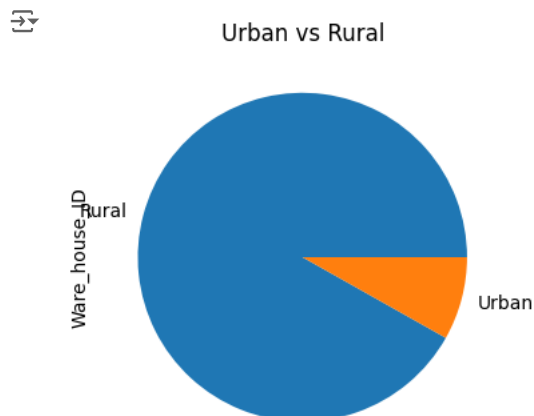
```

warehouse = df.groupby('Location_type')['Ware_house_ID'].nunique()
warehouse

```

```
Location_type
Rural      22957
Urban       2043
Name: Ware_house_ID, dtype: int64
```

```
warehouse.plot(kind='pie', figsize=(7,4))
plt.title('Urban vs Rural')
plt.show()
```

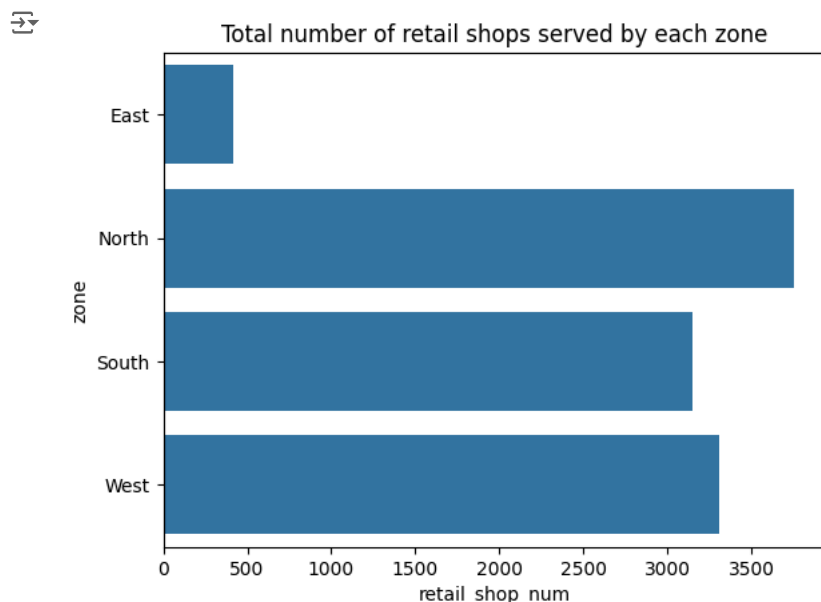


Q3-What is the total number of retail shops served by each zone?

```
no_of_retail_shops = df.groupby('zone')['retail_shop_num'].nunique()
no_of_retail_shops
```

```
zone
East      415
North     3750
South     3145
West      3310
Name: retail_shop_num, dtype: int64
```

```
sns.barplot(x=no_of_retail_shops,y=no_of_retail_shops.index)
plt.title('Total number of retail shops served by each zone')
plt.show()
```



Q4-Calculate the average number of workers per warehouse.

```
avg_workers = df.groupby('Ware_house_ID')['workers_num'].mean()
avg_workers
```

```
Ware_house_ID
WH_100000      29.0
WH_100001      31.0
WH_100002      37.0
```

```

WH_100003    21.0
WH_100004    25.0
...
WH_124995    34.0
WH_124996    28.0
WH_124997     NaN
WH_124998    25.0
WH_124999    39.0
Name: workers_num, Length: 25000, dtype: float64

```

Q5-Determine the percentage of warehouses with electric supply.

```

warehouse = df.groupby('electric_supply')['Ware_house_ID'].nunique()
warehouse

```

```

↗ electric_supply
0      8578
1     16422
Name: Ware_house_ID, dtype: int64

```

Here 0 means there is no power supply in warehouse And 1 means there is power supply

```

pct_warehouse = (warehouse/warehouse.sum())*100 #Here converting values into percentage
pct_warehouse

```

```

↗ electric_supply
0      34.312
1     65.688
Name: Ware_house_ID, dtype: float64

```

```

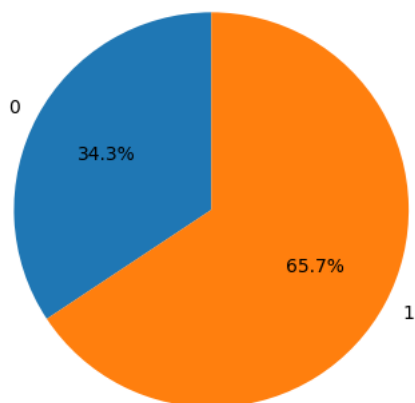
plt.pie(pct_warehouse, labels=pct_warehouse.index, autopct='%1.1f%%', startangle=90)
plt.title('Percentage of warehouses with electric supply')
plt.show()

```

```

↗ Percentage of warehouses with electric supply

```



Q6-What is the average distance of warehouses from the central distribution hub?

```

Avg_distance = df.groupby('WH_regional_zone')['dist_from_hub'].mean()
Avg_distance

```

```

↗ WH_regional_zone
Zone 1    162.361733
Zone 2    162.865677
Zone 3    163.013884
Zone 4    164.709770
Zone 5    163.997602
Zone 6    163.406044
Name: dist_from_hub, dtype: float64

```

Q7-How many warehouses have reported storage issues in the last 3 months?

```

warehouse_issue = df[df['storage_issue_reported_l3m']>0]
warehouse_issue_count = warehouse_issue['Ware_house_ID'].nunique()
warehouse_issue_count

```

```

↗ 24092

```

✓ There are 24092 warehouses that have reported storage issues in last 3 months.

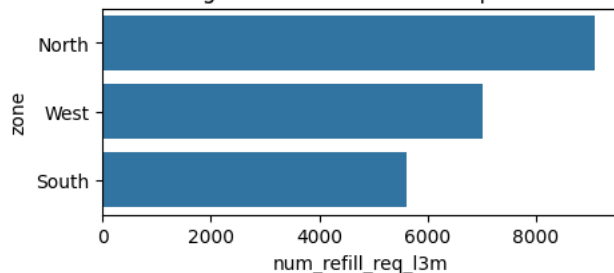
Q8-Identify the top 3 zones with the highest number of refill requests in the last 3 months.

```
refill_request = df[df['num_refill_req_13m']>0]
top_3_zone = refill_request.groupby('zone')['num_refill_req_13m'].count().nlargest(3)
top_3_zone
```

```
zone
North    9086
West     7022
South    5610
Name: num_refill_req_13m, dtype: int64
```

```
plt.figure(figsize=(5,2))
sns.barplot(x=top_3_zone.index,y=top_3_zone.values)
plt.title('Top 3 zones with the highest number of refill requests in the last 3 months')
plt.show()
```

Top 3 zones with the highest number of refill requests in the last 3 months



Q9-Calculate the average number of government checks per warehouse in the last 3 months.

```
avg_govt_check_13m = df.groupby('Ware_house_ID')['govt_check_13m'].mean()
avg_govt_check_13m
```

```
Ware_house_ID
WH_100000    15.0
WH_100001    17.0
WH_100002    22.0
WH_100003    27.0
WH_100004    24.0
...
WH_124995    30.0
WH_124996    18.0
WH_124997    25.0
WH_124998    30.0
WH_124999    11.0
Name: govt_check_13m, Length: 25000, dtype: float64
```

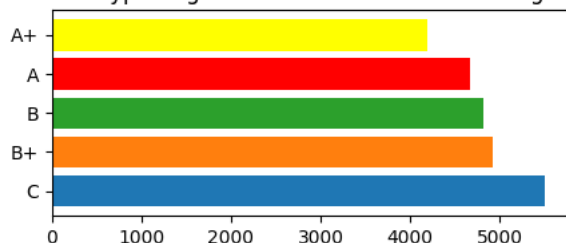
Q10-Determine the most common type of government certification among warehouses.

```
most_common_type = df['approved_wh_govt_certificate'].value_counts()
most_common_type
```

```
approved_wh_govt_certificate
C      5501
B+     4917
B      4812
A      4671
A+     4191
Name: count, dtype: int64
```

```
plt.figure(figsize=(5,2))
colors = ['#1f77b4', '#ff7f0e', '#2ca02c', 'red', 'yellow']
plt.barh(y=most_common_type.index, width=most_common_type.values, color=colors)
plt.title('Most common type of government certification among warehouses')
plt.show()
```

Most common type of government certification among warehouses



Q11- What is the correlation between the number of workers and the number of reported storage issues in the last 3 months?

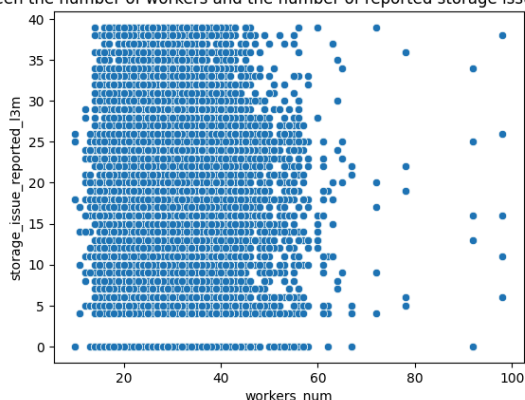
```
workers_and_issues = df[['workers_num', 'storage_issue_reported_13m']]
correlation = workers_and_issues.corr().loc['workers_num', 'storage_issue_reported_13m']
correlation
```

-0.008672981887991375

- ✓ a Pearson correlation coefficient of -0 indicates a negative linear relationship between the number of workers and reported storage issues, suggesting that an increase in workers may correspond with a decrease in reported storage issues

```
sns.scatterplot(x='workers_num', y='storage_issue_reported_13m', data=df)
plt.title('Correlation between the number of workers and the number of reported storage issues in the last 3 months')
plt.show()
```

Correlation between the number of workers and the number of reported storage issues in the last 3 months



Q12-Analyze the relationship between warehouse capacity size and the number of refill requests in the last 3 months.

```
capacity_size = df.groupby('WH_capacity_size')['num_refill_req_13m'].mean()
capacity_size
```

```
WH_capacity_size
Large    4.093815
Mid      4.113473
Small    4.028061
Name: num_refill_req_13m, dtype: float64
```

Q13-Identify which geographical zone has the highest average number of transport issues in the last year.

```
Avg_number = df.groupby('zone')['transport_issue_11y'].mean()
Avg_number
```

```
zone
East    0.790210
North   0.781086
South   0.774599
West    0.762451
Name: transport_issue_11y, dtype: float64
```

Q14 - Calculate the average product weight per ton for warehouses that have temperature regulation machinery.

```
Avg_product_weight_per_ton = df.groupby('temp_reg_mach')['product_wg_ton'].mean()
Avg_product_weight_per_ton
```

```
temp_reg_mach
0    21324.260765
1    23890.774070
Name: product_wg_ton, dtype: float64
```

Q15-Determine the top 5 warehouses with the highest number of government checks in the last 3 months and analyze their storage issue reports.

```
top_5_warehouse= df.nlargest(5, 'govt_check_13m')
compare = top_5_warehouse[['Ware_house_ID', 'govt_check_13m', 'storage_issue_reported_13m']]
compare
```

```
Ware_house_ID  govt_check_13m  storage_issue_reported_13m
63      WH_100063             32                        20
69      WH_100069             32                         9
70      WH_100070             32                        17
85      WH_100085             32                        18
101     WH_100101             32                         8
```

Q16-Compare the average number of workers in warehouses located in urban areas versus rural areas.

```
Avg_no_of_workers = df.groupby('Location_type')['workers_num'].mean()
Avg_no_of_workers
```

```
Location_type
Rural    28.950823
Urban    28.872395
Name: workers_num, dtype: float64
```

Q17-What is the impact of the distance from the hub on the number of transport issues reported?

```
issue_reported = df[['transport_issue_11y', 'dist_from_hub']]
correlation = issue_reported.corr().loc['transport_issue_11y', 'dist_from_hub']
correlation
```

```
0.014335793369184967
```

- A correlation coefficient of 0.01433 between the distance from the hub and transport issues over the last year means that there is no linear relationship between these two variables. In other words, changes in the distance from the hub do not predict or explain changes in the number of transport issues.

Q18-Analyze the effect of competitor presence in the market on the number of refill requests.

```
effect = df[['Competitor_in_mkt', 'num_refill_req_13m']]
correlation = effect.corr().loc['Competitor_in_mkt', 'num_refill_req_13m']
correlation
```

```
0.002984801489494774
```


- A correlation of 0.0029 between the competitor in market and number of refill request last 3 months means that there is no linear relationship between these two variables. In other words, changes in the competitors in market do not predict or explain changes in the number of refill request last 3 months.

Q19-Determine if there is a significant difference in the number of storage issues reported between warehouses with and without government certificates.

```
df['approved_wh_govt_certificate'].fillna('Not Certified', inplace = True) #filling null value with Not Certified
df['approved_wh_govt_certificate'].isnull().sum()
```

 0

```
storage_by_certificate = df.groupby('approved_wh_govt_certificate')['storage_issue_reported_13m'].count()
count_certified = (df['approved_wh_govt_certificate']!='Not Certified').sum()
count_not_certified = storage_by_certificate.get('Not Certified')
print(storage_by_certificate)
print(count_certified)
print(count_not_certified)
```

 approved_wh_govt_certificate

A	4671
A+	4191
B	4812
B+	4917
C	5501
Not Certified	908


Name: storage_issue_reported_13m, dtype: int64
24092
908

```
difference = count_certified - count_not_certified
print(difference) # difference in the number of storage issues reported between warehouses with and without government certificates.
```

 23184


Q20-Investigate the relationship between warehouse establishment year and the number of breakdowns reported in the last 3 months.

```
warehouse = df[['wh_est_year', 'wh_breakdown_13m']]
correlation = warehouse.corr().loc['wh_est_year', 'wh_breakdown_13m']
correlation
```

 -0.3988007362051897

- ✓ A correlation coefficient of -0.039 between the warehouse establishment year and the number of breakdowns reported in the last 3 months indicates that there is a very weak and practically negligible negative linear relationship between these two variables.

```
plt.figure(figsize=(5,2))
sns.scatterplot(x='wh_est_year', y='wh_breakdown_13m', data=df)
plt.title('Relationship between warehouse establishment year and the number of breakdowns reported in the last 3 months')
plt.show()
```

 Relationship between warehouse establishment year and the number of breakdowns reported in the last 3 months
