

Banking Insights for Mining Communities – Jwaneng Branch Case Study#

Introduction

This project analyzes synthetic banking transactions to generate actionable insights for a mining-town branch of FNB Botswana, specifically Jwaneng. Mining communities like Jwaneng have unique payroll cycles, SME activity linked to mine contracts, and digital banking adoption patterns. Understanding these trends can help optimize branch operations, improve SME credit offerings, and enhance customer digital engagement.

DataSet Description

The base dataset is BankSim, a synthetic bank payments simulator developed for fraud detection research. BankSim contains 594,643 transaction records over 180 days, including normal payments and injected fraudulent transactions. It is fully anonymized and publicly available, making it ideal for experimentation and analysis without violating privacy.

BankSim was chosen because it provides realistic banking transactions with sufficient volume and variability, enabling the simulation of mining-town financial behaviors such as payroll-driven transaction spikes, SME loan activity, and digital banking channel usage.

Data Manipulation

```
# -----
# BANKSIM - JWANENG CASE STUDY
# -----

# 1 Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import random
import os
import calendar
from datetime import datetime, timedelta

# Optional for nicer plots
sns.set(style="whitegrid")
plt.rcParams["figure.figsize"] = (12,6)

# -----
# 2 Load Dataset
# -----

df = pd.read_csv("/kaggle/input/banksim1/bs140513_032310.csv") # adjust path if needed
df.info()
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 594643 entries, 0 to 594642
Data columns (total 10 columns):
#   Column          Non-Null Count  Dtype
---  -
0   step            594643 non-null  int64
1   customer        594643 non-null  object
2   age             594643 non-null  object
3   gender          594643 non-null  object
4   zipcodeOri      594643 non-null  object
5   merchant        594643 non-null  object
6   zipMerchant     594643 non-null  object
7   category        594643 non-null  object
8   amount          594643 non-null  float64
9   fraud           594643 non-null  int64
dtypes: float64(1), int64(2), object(7)
memory usage: 45.4+ MB
```

	step	customer	age	gender	zipcodeOri	merchant	zipMerchant	category	amount	fraud
0	0	'C1093826151'	'4'	'M'	'28007'	'M348934600'	'28007'	'es_transportation'	4.55	0
1	0	'C352968107'	'2'	'M'	'28007'	'M348934600'	'28007'	'es_transportation'	39.68	0
2	0	'C2054744914'	'4'	'F'	'28007'	'M1823072687'	'28007'	'es_transportation'	26.89	0
3	0	'C1760612790'	'3'	'M'	'28007'	'M348934600'	'28007'	'es_transportation'	17.25	0
4	0	'C757503768'	'5'	'M'	'28007'	'M348934600'	'28007'	'es_transportation'	35.72	0

```
# -----
# 3 Basic Cleaning
# -----
# Strip quotes from customer and age columns
df['customer'] = df['customer'].str.replace("'", "")
df['age'] = df['age'].str.replace("'", "")

# Convert step to datetime (assume step = days from Jan 1)
start_date = datetime(2025, 1, 1)
df['date'] = df['step'].apply(lambda x: start_date + timedelta(days=x))

# Check for duplicates
df = df.drop_duplicates()

# Reset index
df.reset_index(drop=True, inplace=True)
```

```
# -----
# 4 Add Jwaneng-specific fields
# -----

# 4a) Mark some customers as mine employees
mine_employee_pct = 0.3
df['is_mine_employee'] = df['customer'].apply(lambda x: np.random.rand() < mine_employee_pct)

# 4b) Add synthetic payroll transactions
payroll_transactions = []
salary_min, salary_max = 8000, 28000

for emp in df[df['is_mine_employee']]['customer'].unique():
    for month in range(1, 13): # months 1-12
        last_day = calendar.monthrange(2025, month)[1] # last valid day
        for day in [15, 30]: # payroll dates
            payroll_day = min(day, last_day)
            payroll_transactions.append({
                'step': None,
                'customer': emp,
                'age': np.random.choice(df['age']),
                'gender': np.random.choice(df['gender']),
                'zipcodeOri': 'Jwaneng',
                'merchant': 'Payroll',
                'zipMerchant': 'JWN001',
                'category': 'salary',
                'amount': round(random.uniform(salary_min, salary_max), 2),
                'fraud': 0,
                'date': datetime(2025, month, payroll_day),
                'is_mine_employee': True
            })

payroll_df = pd.DataFrame(payroll_transactions)
df = pd.concat([df, payroll_df], ignore_index=True)

# 4c) Add SMEs
num_smes = 50
sme_list = [f'SME{i:03d}' for i in range(1, num_smes+1)]
sme_industries = ['logistics', 'catering', 'supplies', 'cleaning']

sme_data = []
for sme in sme_list:
    loan_amount = random.randint(20000, 500000)
    repayment_status = random.choices(['on_time', 'late', 'default'], weights=[0.7, 0.2, 0.1])[0]
    credit_score = random.randint(350, 900)
    industry = random.choice(sme_industries)
    sme_data.append({
        'sme_id': sme,
        'industry': industry,
        'loan_amount': loan_amount,
        'repayment_status': repayment_status,
        'credit_score': credit_score
    })

sme_df = pd.DataFrame(sme_data)

# Assign SMEs to random customers
sme_customers = np.random.choice(df['customer'].unique(), num_smes, replace=False)
sme_df['customer'] = sme_customers

# 4d) Add Digital Banking Channels
channels = ['ATM', 'Branch', 'Mobile', 'USSD']
df['channel'] = df.apply(lambda x: np.random.choice(channels, p=[0.3, 0.3, 0.3, 0.1]), axis=1)
```

```
# Increase ATM/Branch usage for payroll transactions
df.loc[df['category']=='salary', 'channel'] = np.random.choice(['ATM','Branch'], p=[0.5,0.5], size=len(df[df['category']=='

# -----
# 5 Fix dates for all transactions
# -----
start_date = datetime(2025,1,1)

# Fill NaT in 'date' using 'step' for original transactions
df['date'] = df.apply(
    lambda row: row['date'] if pd.notnull(row['date']) else start_date + timedelta(days=int(row['step'])),
    axis=1
)

# -----
# 6 Final Checks
# -----
print(df.info())
print(df.head())
print(sme_df.head())

# -----
# 7 Save Prepared Datasets
# -----
df.to_csv("synthetic_jwaneng_prepared.csv", index=False)
sme_df.to_csv("sme_jwaneng.csv", index=False)
print(f"Datasets saved in: {os.getcwd()}")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 693283 entries, 0 to 693282
Data columns (total 13 columns):
#   Column                Non-Null Count  Dtype
---  ---
0   step                   594643 non-null object
1   customer               693283 non-null object
2   age                    693283 non-null object
3   gender                 693283 non-null object
4   zipcodeOri             693283 non-null object
5   merchant               693283 non-null object
6   zipMerchant            693283 non-null object
7   category               693283 non-null object
8   amount                 693283 non-null float64
9   fraud                  693283 non-null int64
10  date                   693283 non-null datetime64[ns]
11  is_mine_employee       693283 non-null bool
12  channel                693283 non-null object
dtypes: bool(1), datetime64[ns](1), float64(1), int64(1), object(9)
memory usage: 64.1+ MB
None
```

	step	customer	age	gender	zipcodeOri	merchant	zipMerchant
0	0	C1093826151	4	'M'	'28007'	'M348934600'	'28007'
1	0	C352968107	2	'M'	'28007'	'M348934600'	'28007'
2	0	C2054744914	4	'F'	'28007'	'M1823072687'	'28007'
3	0	C1760612790	3	'M'	'28007'	'M348934600'	'28007'
4	0	C757503768	5	'M'	'28007'	'M348934600'	'28007'

	category	amount	fraud	date	is_mine_employee	channel
0	'es_transportation'	4.55	0	2025-01-01	False	USSD
1	'es_transportation'	39.68	0	2025-01-01	False	ATM
2	'es_transportation'	26.89	0	2025-01-01	False	Mobile
3	'es_transportation'	17.25	0	2025-01-01	False	ATM
4	'es_transportation'	35.72	0	2025-01-01	False	ATM

	sme_id	industry	loan_amount	repayment_status	credit_score	customer
0	SME001	cleaning	460128	late	565	C1351458855
1	SME002	catering	63035	on_time	860	C2001133685
2	SME003	cleaning	402467	late	590	C1058213633
3	SME004	catering	273548	on_time	447	C469822988
4	SME005	catering	424555	on_time	517	C746862122

Datasets saved in: /kaggle/working

▼ Data Analysis

```
# -----
# 2 Load Prepared Datasets
# -----
df = pd.read_csv("synthetic_jwaneng_prepared.csv", parse_dates=['date'])
sme_df = pd.read_csv("sme_jwaneng.csv")

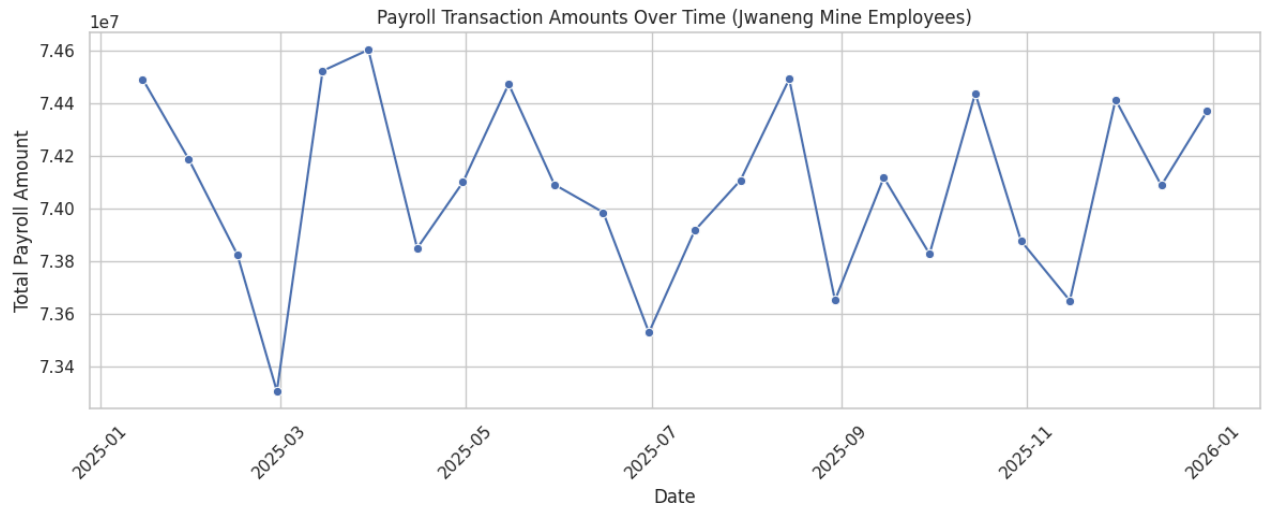
# -----
# 3 Payroll Transaction Analysis
# -----
# Filter payroll transactions
payroll_df = df[df['category'] == 'salary']
```

```
# Aggregate by date
payroll_daily = payroll_df.groupby('date')['amount'].sum().reset_index()

# Plot payroll spikes
plt.figure(figsize=(12,5))
sns.lineplot(data=payroll_daily, x='date', y='amount', marker='o')
plt.title("Payroll Transaction Amounts Over Time (Jwaneng Mine Employees)")
plt.xlabel("Date")
plt.ylabel("Total Payroll Amount")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Optional: Top 10 highest payroll days
top_paydays = payroll_daily.sort_values(by='amount', ascending=False).head(10)
print("Top 10 payroll days by total amount:")
print(top_paydays)
```

```
/usr/local/lib/python3.11/dist-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will
with pd.option_context('mode.use_inf_as_na', True):
/usr/local/lib/python3.11/dist-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will
with pd.option_context('mode.use_inf_as_na', True):
```



Top 10 payroll days by total amount:

	date	amount
5	2025-03-30	74601561.50
4	2025-03-15	74521511.52
14	2025-08-15	74490490.18
0	2025-01-15	74490175.78
8	2025-05-15	74471561.00
18	2025-10-15	74436541.37
21	2025-11-30	74412341.94
23	2025-12-30	74368403.58
1	2025-01-30	74188476.89
16	2025-09-15	74116866.94

✓ Payroll Transaction Spikes

The line chart above shows the total payroll transaction amounts for mine employees over time. Notice the clear spikes on the 15th and end of each month, corresponding to payday cycles.

Insight:

- FNB Jwaneng can anticipate high transaction volumes around these dates.
- Scheduling staff and cash/ATM replenishment around these dates can improve service efficiency.
- The bank could offer payday-linked micro-loans or digital savings campaigns to employees.

```
# -----
# 4 SME Financing Trends
# -----
# Count SMEs by repayment status
repayment_counts = sme_df['repayment_status'].value_counts()

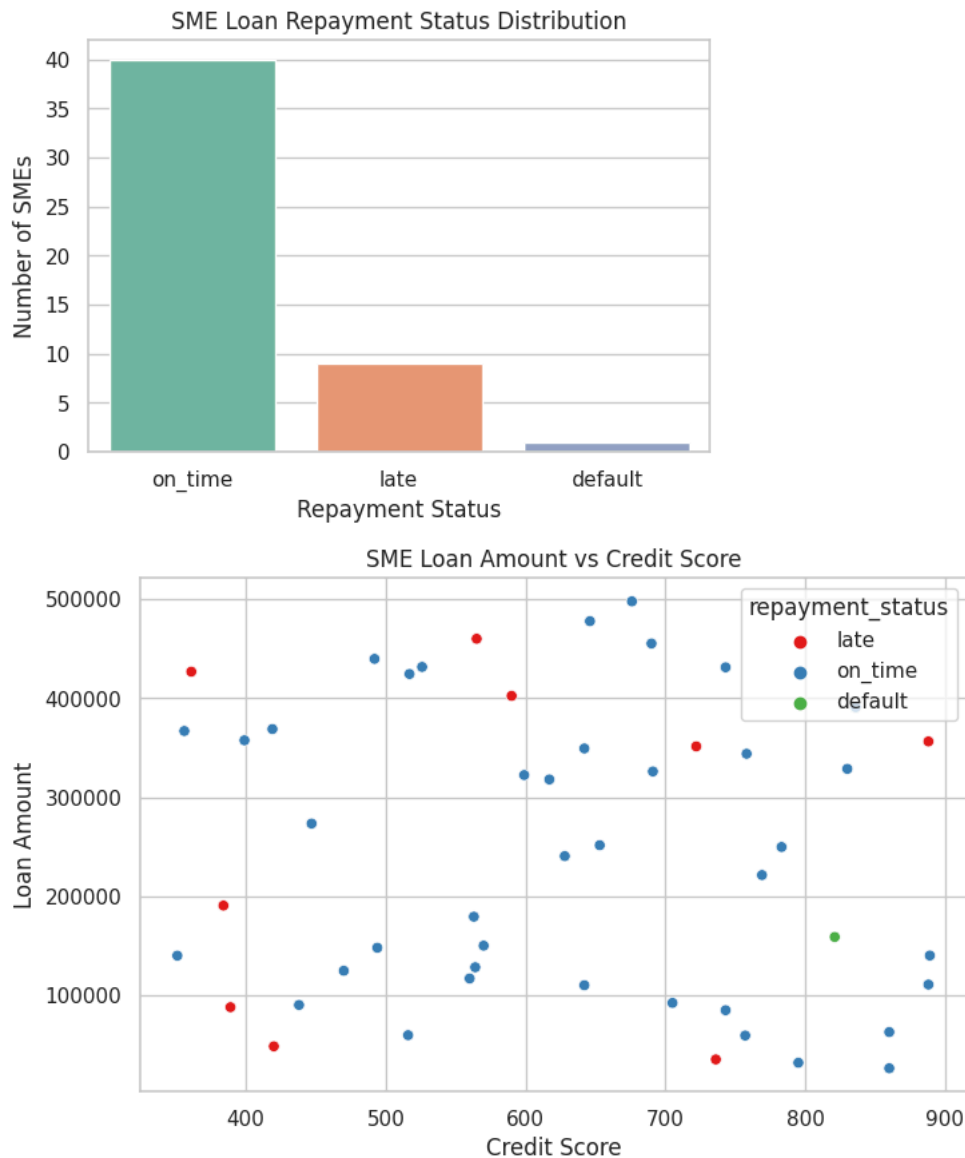
plt.figure(figsize=(6,4))
```

```

sns.barplot(x=repayment_counts.index, y=repayment_counts.values, palette="Set2")
plt.title("SME Loan Repayment Status Distribution")
plt.xlabel("Repayment Status")
plt.ylabel("Number of SMEs")
plt.show()

# Loan amount vs credit score scatter
plt.figure(figsize=(8,5))
sns.scatterplot(data=sme_df, x='credit_score', y='loan_amount', hue='repayment_status', palette="Set1")
plt.title("SME Loan Amount vs Credit Score")
plt.xlabel("Credit Score")
plt.ylabel("Loan Amount")
plt.show()

```



SME Loan Repayment Behavior

The bar chart shows the distribution of SME loan repayment status (on-time, late, default). The scatter plot shows how loan amount relates to credit score.

Insights:

- Most SMEs repay on time, but a small percentage are late or default.
- Higher credit scores generally correlate with timely repayment, but there are exceptions.
- FNB could use these insights to refine SME loan risk models and offer credit products tailored to industry type or repayment reliability.

```

# -----
# 5 Digital Banking Adoption
# -----
# Count transactions by channel
channel_counts = df['channel'].value_counts()

```

```
plt.figure(figsize=(6,4))
sns.barplot(x=channel_counts.index, y=channel_counts.values, palette="Set3")
plt.title("Transaction Counts by Banking Channel")
plt.xlabel("Channel")
plt.ylabel("Number of Transactions")
plt.show()

# Channel usage for payroll transactions specifically
payroll_channels = payroll_df['channel'].value_counts()

plt.figure(figsize=(6,4))
sns.barplot(x=payroll_channels.index, y=payroll_channels.values, palette="Set1")
plt.title("Payroll Transaction Channels (Mine Employees)")
plt.xlabel("Channel")
plt.ylabel("Number of Transactions")
plt.show()
```



✓ Digital Banking Channels

The bar chart shows the number of transactions by channel, while the payroll-specific chart highlights how mine employees use ATMs and branches for salary withdrawals.

Insights:

- ATM and branch usage dominates payroll withdrawals.
- Mobile and USSD channels are underutilized for salary transactions, suggesting an opportunity to promote digital banking adoption among mine employees.
- FNB could implement targeted campaigns or incentives to increase mobile banking usage, reducing branch congestion and operational costs.

```
# -----
# 6 Summary Insights (print)
# -----
```

```
num_mine_employees = df['is_mine_employee'].sum()
num_smes = len(sme_df)
total_transactions = len(df)
total_payroll = payroll_df['amount'].sum()

print(f"Total transactions: {total_transactions}")
print(f"Mine employees: {num_mine_employees}")
print(f"Total payroll distributed: BWP {total_payroll:,.2f}")
print(f"Total SMEs analyzed: {num_smes}")
```

```
Total transactions: 693283
Mine employees: 277554
Total payroll distributed: BWP 1,777,892,208.79
Total SMEs analyzed: 50
```