Journal of Advances in Mathematical & Computational Sciences
An International Pan-African Multidisciplinary Journal of the SMART Research Group
International Centre for IT & Development (ICITD) USA
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Empirical Study: Machine Learning Analytics of Automated Teller Machines Data for Enhanced Customer Satisfaction and Banking Service Integrity in Nigeria

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ABSTRACT

Automated Teller Machines (ATMs) are ubiquitous in modern banking and generate large volumes of data on user behavior and preferences. This study analyzed big data from ATMs to identify patterns in ATM usage, observe potential fraud, and optimize ATM placement and maintenance. Data were collected from several banks in Nigeria; covering over 2 million ATM transactions conducted over a one-year period, including device status logs. Our analysis reveals several key findings, including the importance of proximity to users' home, work, and market locations in ATM placement, the devices responsible for service downtime, the possibility of fraudulent transactions involving identity theft, and the potential for personalized marketing campaigns based on user demographics and transaction history. ATM patronage during active hours was observed between 9 am and 7 pm, with cash withdrawal being the major transaction for most customers, typically ranging between ₦2,000 and ₦40,000. Additionally, network fluctuations (65.8%), card reader issues (18.2%), cash jams (11%) and PIN pad (5%) issues were identified as major contributors to ATM downtime. Lastly, ATM fraud typically occurs outside customers' proximity and transaction patterns. These insights have important implications for banks and other financial institutions seeking to improve their services and maximize customer satisfaction.

Keywords: ATM, Machine Learning, Unsupervised Learning, Big data, Transaction Monitoring

Ojulari, H.O., Oke, A.O. & Arulogun, O.T. (2024): Empirical Study: Machine Learning Analytics of Automated Teller Machines Data for Enhanced Customer Satisfaction and Banking Service Integrity in Nigeria. Journal of Advances in Mathematical & Computational Science. Vol. 12, No. 1. Pp 87-102. Available online at www.isteams.net/mathematics-computationaljournal.
dx.doi.org/10.22624/AIMS/MATHS/V12N2P6

1. INTRODUCTION

In Nigeria, banking industry is a critical component of the nation's economy, enabling individuals and businesses to manage their finances and access credit. Automated Teller Machines (ATMs) play a vital role in the banking system, providing customers with access to their accounts and a range of banking services. As the use of ATMs has grown in Nigeria, they generate vast amounts of data on user behavior and preferences. ATMs have revolutionized banking by providing customers with convenient, 24/7 access to cash and other financial services. In a general term, big data is an extremely large collection of data (structured or unstructured) that grows exponentially with time. The extremely large collection in this context means the dataset is too large to reasonably process or store with traditional tooling or on a single computer (Justin, 2016). The amount of data generated by the global population daily sums up to 2.5 quintillion bytes (Rohit, 2019).

However, the widespread use of ATMs has also generated vast amounts of data on user behavior and preferences. This data, commonly referred to as "ATM big data," has the potential to be used for a variety of purposes, including improving ATM placement and maintenance, detecting, and preventing fraud, and personalizing marketing and advertising campaigns for banking products and services. Thus, ATM big data means a huge ATM transaction data collected over time, and this data varies significantly from different banks. The volume of data generated in the banking or financial sector is highly enormous. The innovative use of ATM in service delivery has led to the exponential growth of transaction data. Financial services are using big data analytics to store data, derive business insights, and improve scalability. Thus, this provides better solutions for investment management. Nigerian banks use the results of big data analytics to make business decisions accordingly.

The potential difficulty in handling such a large amount of data is because of a rapid increase in data volume compared to the computing resources (Katal *et al*, 2013) and the limited knowledge of what the data can be used for. Nevertheless, conventional methods are usually impossible to determine the underlying relationship or connections in the big data system (Justin, 2016). The bankers use the behavioral patterns contained in the data to manage customer value and strategies in areas (Vladimir, 2018) like discovering the withdrawing patterns of the customers, identifying the main channels of transactions i.e., ATM withdrawal, Point of Sales (POS), splitting the customers into segments according to their profiles, product cross-selling based on the customers' segmentation, fraud management and prevention, risk assessment, and customer feedback analysis.

This paper harnesses the power of ATM big data to revolutionize banking services in Nigeria, focusing on critical areas such as ATM placement, cash management, product advertisement, and overall enhancement of customer satisfaction. Through meticulous analysis of the vast datasets generated by ATMs, we delve deep into understanding user behavior, transaction patterns, and preferences. These insights unveil invaluable opportunities for banks and financial institutions to optimize their services. For instance, by scrutinizing ATM usage data, we identify prime locations for ATM placement, ensuring convenient accessibility for customers while maximizing operational efficiency. Moreover, our analysis of cash withdrawal patterns allows for more effective cash management strategies, reducing the likelihood of cash shortages or surpluses at ATMs.

Furthermore, leveraging customer transaction histories obtained from ATM data enables targeted product advertisement campaigns. By tailoring offerings based on individual preferences and spending habits, banks can enhance customer engagement and drive product adoption rates. In addition to these operational optimizations, our study emphasizes the paramount importance of enhancing customer satisfaction. By gaining a comprehensive understanding of customer behavior and preferences through ATM big data analysis, banks can tailor their services to meet and exceed customer expectations. This includes personalized banking experiences, proactive issue resolution, and the implementation of innovative service enhancements. In essence, the insights gleaned from ATM big data analysis serve as a catalyst for transformative changes within the banking sector, driving efficiency, profitability, and ultimately, ensuring unparalleled customer satisfaction.

Statistical models such as linear regression, logistic regression, classification trees, and other more recently developed methods could be applied in big data analytics (Thomas *et al*, 2005). Besides, having models to predict the outcomes of big data analytics is not new in retail banking. A scorecard as an example has been in use in the 1960s to predict likely defaulters (Brentnall *et al*, 2008). ATM big data is an exciting field in ATM technology and business. Depending on the growing customer demands or needs regarding financial services, the volume of transactions performed bank-wide results in large datasets which present new operational, security, and business challenges to both banks and their customers (Stacy, 2014). Figure 1 shows different potential uses or applications of ATM big data such as cash management, monitoring, advert and campaigns management, fraud detection, reconciliation and dispute resolutions, user footage analysis, and ATM placement.

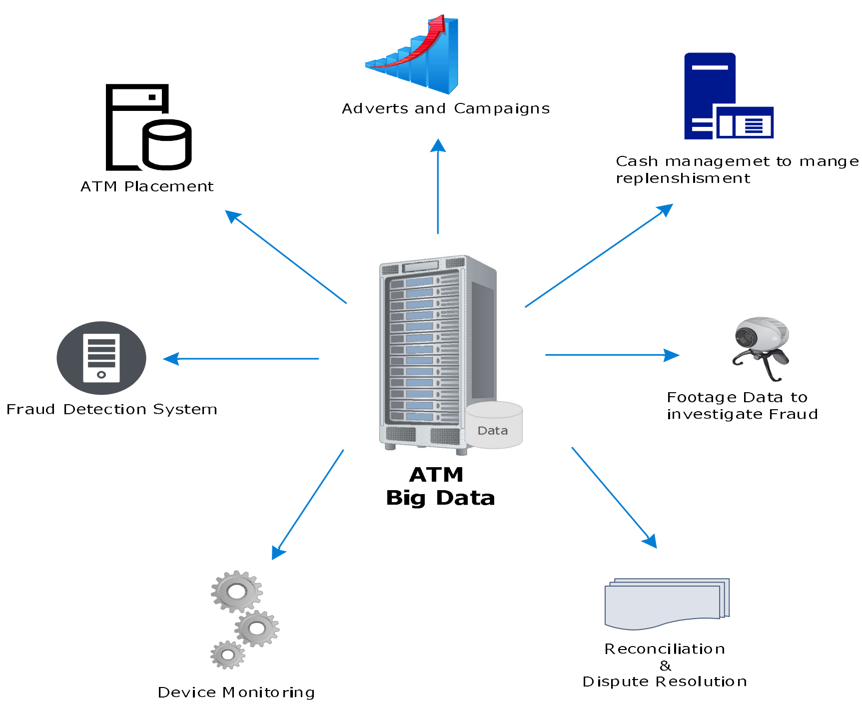

Fig 1: ATM Big Data Applications

2. LITERATURE REVIEW

Previous research has demonstrated the value of big data in the banking industry. Studies have shown that the use of big data analytics could help banks optimize their services, detect, and prevent fraud, and improve customer satisfaction (Bose *et al.,* 2019; Kshetri *et al*., 2020). In Nigeria, several studies have explored ATM usage and customer behavior, highlighting the importance of ATM placement, accessibility, and security (Akinwale et al., 2020; Bello *et al*., 2018). However, there is a need for more extensive research on the use of ATM big data to improve ATM services such as availability of the machine, cash demand, ATM security, customized banking products to enhance Nigeria customer satisfaction.

Velivasaki, Athanasoulis, and Trakadas (2019) designed an ATM cash management system running on cloud analytics appliances to manage ATM replenishment based on cash demand using data-intensive techniques. The authors described the challenges of managing cash in ATMs, including the need for timely and accurate replenishment, minimizing the risk of theft or robbery, and optimizing the use of cash in ATMs. The study developed a system called uCash that used data analysis, machine learning such as Random Forests (RF) and Support Vector Machines (SVM), and optimization algorithms to predict cash demand in ATMs and optimize cash replenishment to address these challenges.

The performance was evaluated using simulations and real-world data from a bank in Greece, but there was a limitation of not providing a detailed description of the performance metrics used to evaluate uCash system to assess its effectiveness. However, the work stressed on using ATM customer transaction volume to predict cash demand and replenishment. Maervoet *et al.*, (2012) said the spending profile of a cardholder identifies the customer spending behavior. And that forms the dataset for the machine learning model. The study categorized cardholders into three groups based on the spending habits of customers as a high-spending group, a medium-spending group, and a low-spending group. The spending profile of a customer is analyzed using the K-Means clustering algorithm as it groups data based on similar attribute values; this classification helps the banks to make decisions.

The operations support team in the bank utilizes hardware data analytics to improve ATM availability and lower support and maintenance costs of the hardware devices. Poor service delivery to customers is a result of low ATM availability and performance. Using the failure rate data of hardware components helps predict how often the hardware devices develop faults and their impact on the Key Performance Index (KPI). Most transaction failures or ATM availability issues are TCP/IP network related, such as connection time outs or application response time issues. The impact of the ATM downtime on customer experience and profitability during a peak period (high traffic) will be higher than a less-busy period of lower traffic (Stacy, 2016). ATM is a composite of multiple devices or components, and its availability depends on the proper functioning of these devices. Device Error Data contains in detail error each device encounters during transactions.

As availability policies continue to expand and evolve, data retrieval and analytics become crucial to improve the customer's experience on the ATM. This availability has gone beyond the ATM uptime and downtime measures as a result of network connectivity. Other associated devices need inclusive consideration in the metrics. Such devices directly or indirectly interact with customers during transactions; these are Card Reader, Screen, PIN Pad, Cash Dispenser and Presenter, Item Processing, and Cassettes. These devices should be subjected to monitoring to improve the customer experience. Each hardware device has error codes, status codes, and event handlers.

There have been few software analytics tools, in this regard, that some banks are using globally to monitor transactions and hardware devices with analytic displays on the dashboards. Such software tools are NCR Aptra Vision, NCR Gasper, NCR OptiCash, Splunk, HP Operations Manager, INETCO, or IBM Tivoli. These tools provide data analytics directly from transaction data to harvest deeper insights across the ATM network (Stacy, 2016). Mining transaction data could help to manage running bank adverts, products, or third-party adverts. Many organizations recognize the importance of leveraging advanced technologies to implement efficient fraud detection systems, thereby preventing fraudulent transactions (Rangineni and Marupaka, 2023).

3. RESEARCH METHODOLOGY

The research adopted an exploratory technique using observational method to examine what entails in ATM big data. ATM data could come from customer transaction data logs, device error logs and trace logs for tracking ATM daily activities. The ATM data that were examined as part of ATM big data paradigms namely are customer transaction log in electronic journal (EJ) and transaction logs and device statuses in device error data and trace logs which combine both transaction and device traces. Device status logs could be used to manage ATM preventive maintenance and Mean Time Between Failure (MTBF) of each associated device. Figure 1 shows different potential uses or applications of ATM big data such as cash management, monitoring, advert and campaigns management, fraud detection, reconciliation and dispute resolutions, user footage analysis, and ATM placement. Customer transactions on the ATM network collectively run into billions of data yearly per bank based on customer's size. The ATM big data that were investigated are described as follows.

3.1 Customer transaction log data

A substantial dataset comprising ATM transactions conducted over a period of one-year, detailing user transaction patterns from multiple banks in Nigeria, was gathered for data analytics. These transactions are stored by ATMs during state transitions in a semi-structured text file known as an Electronic Journal (EJ). An EJ file is a dual-entry document containing both ATM flow and Host Server messages in a guided format. The state transition within an ATM represents the sequential flow of ATM transactions. The file contains customer transactions of different transaction types, transaction datetime, transaction amount, the ATM identity, error codes, and transaction comments. An example of a withdrawal transaction data from a sample EJ is illustrated in Figure 2, where "TRANSACTION START" indicates the initiation of a transaction event within a session, while "TRANSACTION END" denotes its termination.

A transaction session (or cycle) encompasses a complete transaction(s) from card insertion to ejection, though multiple transactions can occur within a single session based on customer choice. Hence, customers can decide to perform multiple transactions (transaction selection on the ATM screen) within a session. These transactions range from cash withdrawal, cash deposit, balance inquiry, mobile top-up, bill payment, fund transfer, third-party payment, Quickteller, mini statement, advance prepaid, etc. The sequence (or flow) of transaction states is downloaded onto the ATM from the host server before customer usage. In other words, the host server is responsible for sending "ATM download" to all ATM terminals connected to the same network. The volume and expansion of financial services result in the exponential growth of customer transaction data over time

The transaction data was extracted from the EJ using regular expressions and prepared for data analytics, as outlined in Ojulari *et al*. (2017). Various statistical and machine learning techniques, including K-mode clustering, deep learning networks, linear, and non-linear regression analyses, were employed to analyze customer transaction data. RStudio's visualizer facilitated graphical analysis to identify patterns in user behavior and preferences. The list of data features captured from EJs is shown as follows:

- Transaction date and time
- Terminal ID
- ATM location (BranchCode)
- Type of transaction (e.g., withdrawal, deposit, transfer, bill payment, third party transfer)
- Transaction Amount
- Card No (to identify individual customers)
- Transaction status (Success or failure)
- Comment (Reason for failure or transaction remark)
- Time spent at ATM (duration)
- Transaction Trace – cassette level
- Error code – to know the cause of transaction failure.
- Security camera footage

```
29/12/2014 06:42:01 TRANSACTION START
29/12/2014 06:42:04 CAMERA - PICTURE TAKEN
29/12/2014 06:42:04 CAMERA - PICTURE TAKEN
29/12/2014 06:42:04 REPLY RECV
29/12/2014 06:42:05 TRANSACTION DATA (SET NEXT STATE PRINT)
 [TRANSACTION RECORD]
 OPCode            [ACID   ]
 Function ID       [5]                                        ATM Message
 Card Number               [519911XXXXXX9120]
 Amount            [000000000000]
 Trans SEQ number          [3944]
 Error Code        [0000000]
 JPR CONTENTS
++++++++++++++++++++++++++++++++++++++++++++++
   29\12\14    06:42    12325322

CARD NUMBER...........9120
3944
???------------------------------------                       Host Message
---
++++++++++++++++++++++++++++++++++++++++++++++

29/12/2014 06:42:20 PIN ENTERED
29/12/2014 06:42:28 CAMERA - PICTURE TAKEN
29/12/2014 06:42:32 REPLY RECV
29/12/2014 06:42:42 CASH DISPENSER - PRESENTED
29/12/2014 06:42:44 CASH DISPENSER - ITEM TAKEN
29/12/2014 06:42:44 TRANSACTION DATA (COMPLETED)
 [TRANSACTION RECORD]
 OPCode            [ACDDAB ]
 Function ID       [2]
 Card Number               [519911XXXXXX9120]
 Amount            [000000100000]
 Denomination      [a,a,B,B]
 Request Count     [0,2,0,0]
 Dispense Count    [0,0,2,0]                                  ATM Message
 Remain Count      [0,0,862,854]
 Pick-up Count     [0,0,2,0]
 Reject Count      [0,0,0,0]
 Trans SEQ number          [3945]
 Error Code        [0000000]
 Present Amount    [000000100000]
 Present Time      [29/12/2014 06:42:42]
 Taken Amount      [000000100000]
 Taken Time        [29/12/2014 06:42:44]
 JPR CONTENTS
++++++++++++++++++++++++++++++++++++++++++++++
   29\12\14    06:42    12325322

CARD NUMBER...........9120
3945   003945
WITHDRAW         NGN1000.00
FROM 5987                                                     Host Message
LEDGER      NGN26933.65
AVAIL       NGN26933.65
---------------------------------------

++++++++++++++++++++++++++++++++++++++++++++++
```

Figure 2. EJ Transaction Sample
(Ojulari *et al.*, 2017)

Analysing transaction data to understand customer behaviour was crucial for making informed decisions. After data extraction and preparation, the transaction data was segmented using hierarchical clustering technique by grouping the dataset into customer-clustered data profile. The customer-clustered data was segmented further using spatial clustering technique based on proximity. Transaction monitoring, cash management, and fraud detection were examined for data analytics. For transaction monitoring and location tracking, ATM location was resolved into BranchCode. However, geospatial analysis (location coordinates) using geocoding technique was essential for identifying proximity to specific places. Additionally, proximity analysis was employed to calculate distances between transaction coordinates and known home coordinates. Hence, classification method using regression was adopted to train a classifier to categorize transactions as “home”, “work”, “market” or “others” based on proximity. Setting a threshold of 1km, transaction volumes based on proximity category were obtained for individual customers. This helped to track customer transaction and location.

Cash management utilized a combination of transaction data and cassette components to determine when cash levels are low and require replenishment. Cash monitoring in ATM systems typically involves tracking the cash levels, transaction volumes, and other relevant metrics to ensure that ATMs are adequately stocked with cash and to optimize cash management processes. Figure 3 shows the cassette levels in the transaction log. Every ATM is deployed, by default, with four cassettes (cash containers for cash dispenser module) and configured for different currency note denominations. A typical sample of cassette is shown in Figure 4. Regular expression (Regex) was applied to the Transaction Log to extract cassette level details at the end of each transaction session (cycle) and validate them against the individual cash level thresholds. The dataset was analyzed to identify trends and patterns in cash withdrawals over time. This helped in predicting future cash demands and scheduling cash replenishments accordingly. A threshold-based monitoring was applied by setting threshold for cash levels in ATMs. When cash levels fall below a certain threshold, alerts are triggered to prompt cash replenishment activities to ATM custodians and channel managers in banks.

Fraud detection management was analyzed using autoencoder deep learning on the EJ data to study regular transaction patterns of valid customers and prevent malicious transactions on individual accounts through the ATM channel. The autoencoder deep learning models employed unsupervised learning techniques, as Nigerian banks do not maintain records of fraudulent transaction cases. Fraud detection can be further enhanced by utilizing ATM footage to identify perpetrators. Additionally, leveraging National Identity Number (NIN) or Bank Verification Number (BVN) biometric databases can aid in the identification and arrest of these perpetrators.

3.2 Device Error and Trace Logs

Monitoring the hardware device events helps to detect or track fault occurrence on the hardware. It determines the Mean Time Between Failure (MTBF) or the failure rate of the associated devices to aid successful transactions on ATM. Supervised learning techniques such as random forest, decision tree, artificial neural network (ANN), k nearest neighbours (KNN) were found to be useful to predict or forecast the statuses of these devices based on the historical data in the device logs. The following data features were considered in the device error: DeviceName, Month, Day, Hour, ErrorCode, and StatusCode. DeviceStatus was added as the output field as binary variable of either 0 or 1 (0 – success and 1 – failure). The trace log shown in Figure 5 is a rich repository for diagnosing and tracing failed transactions on ATM. It is usually a text file in a particular format like EJ, and it is referred to as a debug file. The file contains detailed information on the failure points of the concerned transactions revealing the responsible hardware components and the actual failure reason. Mining the trace log file for data analytics provides a handy tool to predict and manage the occurrence of such failures technically.

```
time='8:59:53 AM';date=11/3/21;type=Log;message='EDC CLEAR';
time='8:59:59 AM';date=11/3/21;type=Log;message='UNLOCK CASSETTE';
time='8:59:59 AM';date=11/3/21;type=Log;message='EXCHANGE CASSETTES';
time='9:00:01 AM';date=11/3/21;type=Log;message='TEST DISPENSER';
time='9:00:08 AM';date=11/3/21;type=Log;message=CDM_InitD0030;
time='9:00:08 AM';date=11/3/21;type=Log;message=CDM_CassSatusD0030000000000001:00002:00003:00004;
time='9:00:08 AM';date=11/3/21;type=Log;message='cassetteStatus <1=?=?=?';
time='9:00:16 AM';date=11/3/21;type=Log;message='Chest door closed';
time='9:00:20 AM';date=11/3/21;type=Log;message='RPrinter status P10020Reset status P10020';
time='9:00:20 AM';date=11/3/21;type=Log;message='          LOADED  DISP. RETRAC TST DIV';
time='9:00:20 AM';date=11/3/21;type=Log;message='CASSETTE 1   5000      0      0      0';
time='9:00:20 AM';date=11/3/21;type=Log;message='CASSETTE 2      0      0      0      0';
time='9:00:20 AM';date=11/3/21;type=Log;message='CASSETTE 3      0      0      0      0';
time='9:00:20 AM';date=11/3/21;type=Log;message='CASSETTE 4      0      0      0      0';
time='9:00:20 AM';date=11/3/21;type=Log;message='                          REMAINING';
time='9:00:20 AM';date=11/3/21;type=Log;message='CASSETTE 1                     5000';
time='9:00:20 AM';date=11/3/21;type=Log;message='CASSETTE 2                        0';
time='9:00:20 AM';date=11/3/21;type=Log;message='CASSETTE 3                        0';
time='9:00:20 AM';date=11/3/21;type=Log;message='CASSETTE 4                        0';
time='9:00:20 AM';date=11/3/21;type=Log;message='DIVERTED BILLS 0';
time='9:00:20 AM';date=11/3/21;type=Log;message='RETAINED CARDS 0';
time='9:00:20 AM';date=11/3/21;type=Log;message='TRANSACTION COUNT 10369';
time='9:00:20 AM';date=11/3/21;type=Log;message='BILL COUNTERS LAST CLEARED
        TIME:09:00:00 DATE: 03.11.2021';
time='9:00:20 AM';date=11/3/21;type=Log;message='HARDWARE COUNTERS';
time='9:00:20 AM';date=11/3/21;type=Log;message='DIVERTED 0';
Ln 23, Col 77   511,794 characters
```

Figure 3. Transaction Log detailing Cassette Counts

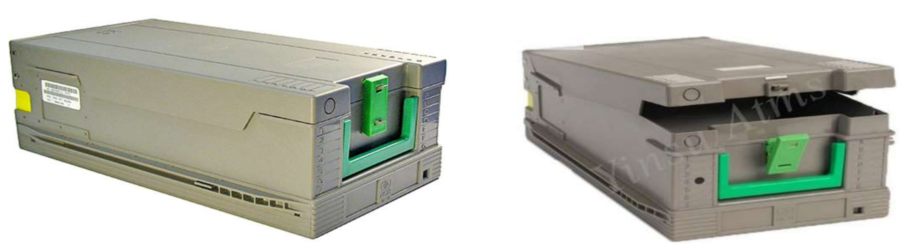

Figure 4. ATM Cassettes (Cash Container)

This data can be used for preventive maintenance of the ATM to reduce transaction failure rates. The machine learning technique requires to predict the occurrence of failed transactions is supervised learning.

3.3 Ethical Considerations

This work adhered to ethical standards, ensuring the confidentiality and privacy of individual transactional data. However, the data were retrieved from a test data repository server containing masked card number transactions. The study complied with relevant data protection regulations and institutional ethical guidelines, such as the General Data Protection Regulation (GDPR) and the Payment Card Industry Data Security Standard (PCI DSS), to adhere to consumer protection policies.

```
TRACE211101.log - Notepad
File  Edit  Format  View  Help
2021-11-01 02:59:01.610 Receive restart Ascreen message.
2021-11-01 02:59:05.869 Restart AScreen process.
2021-11-01 02:59:05.879 send message to screen failed,need restart AScreen
2021-11-01 02:59:15.879 send message to screen failed,need restart AScreen
2021-11-01 02:59:25.909 SCREEN NAME: 006
2021-11-01 06:20:17.152 CardReader::IDC_CARDREAD Event szRecvData:0
2021-11-01 06:20:17.152 CardReader::IDC_CARDREAD m_bCardRealRead = TRUE
2021-11-01 06:20:17.313 iDetectCard g_bIsCardInsert:1
2021-11-01 06:20:17.395 l_iTrack=7
2021-11-01 06:20:17.396 OInService::bIsICCard Return(0).
2021-11-01 06:20:17.396 PMXPN = 10, PINPD = 0F
2021-11-01 06:20:18.637 EXIT ZERO STATE.
2021-11-01 06:20:18.741 STATE 'D': 136
2021-11-01 06:20:18.741 STATE TYPE04 (Set OPCode)->
2021-11-01 06:20:18.745 #ABDABD  #
2021-11-01 06:20:18.829 STATE 'I': 137
2021-11-01 06:20:18.829 STATE TYPE09 (SEND TRANSACTION REQUEST MSG)->
2021-11-01 06:20:18.832 STATE Process ADA Verification->
2021-11-01 06:20:18.895 SCREEN NAME: 046
2021-11-01 06:20:18.919 TXN_MAGNETIC Request Message Sent.
2021-11-01 06:20:18.919 CREATING TRANSACTION REQUEST MSG..
2021-11-01 06:20:18.919         LUNO: 050
2021-11-01 06:20:18.919         Time Variant Number: N/A
2021-11-01 06:20:18.919         Top of Receipt Transaction Flag: will print data for this transaction at the top of the receipt
2021-11-01 06:20:18.920         Message Co-Ordination Number: 3
2021-11-01 06:20:18.930         Operation Code Data: ABDABD
2021-11-01 06:20:18.930         Amount Entry Field: 000000000000
2021-11-01 06:20:18.930         PIN Buffer(Buffer A):
2021-11-01 06:20:18.930         General Buffer B:
2021-11-01 06:20:18.930         General Buffer C:
2021-11-01 06:20:18.970 Timeout Seconds(185000).
2021-11-01 06:20:22.895 OProcFunction::iSetFuncCmdMsg->EMV RESP DATA:
2021-11-01 06:20:22.895         ARC: 0000
2021-11-01 06:20:22.896         IAD:
2021-11-01 06:20:22.896         SCP:
2021-11-01 06:20:22.896         AUC:
```

Figure 5. Trace Log Sample

4. EXPERIMENTAL FINDINGS

In Figures 6, 7, and 8, the TransType categories are Cash Withdrawal (3), Bill Payment (6), and Fund Transfer (7). Other TransType categories not depicted in the figures include Inquiry (1), Mini Statement (2), Third Party (4), and QuickTeller (5). Figure 6 displays daily transaction distributions, while Figure 7 shows monthly transaction distributions, with cash withdrawal being the most frequent transaction type. Figure 8 illustrates that transactions within the range of ₦2,000 to ₦40,000 were the most common, as also shown in Table 1. The analysis of ATM big data in the Nigerian banking industry yielded several key findings as follows.

1. Transaction monitoring analysis revealed that cash withdrawals were commonly conducted by many bank customers, primarily in the vicinity of their 'Home' and 'Work' locations, with fewer transactions occurring at 'Other' locations. Conversely, fund transfers were more frequently initiated at 'Work' and 'Other' locations. Proximity was a strong predictor of ATM usage with users preferring to use ATMs that were close to their daily commute. In a nutshell, most customers prefer using ATMs located near their usual destinations. This suggests that banks should prioritize ATM placement in areas that are convenient for their customers, rather than simply maximizing the number of ATMs in a given area. Also, most ATM transactions in Nigeria occur during business hours on weekdays as shown in Table 2, indicating the importance of ATM accessibility during active hours (9am – 7pm) and should be always loaded with cash.

Table 1. TransType Frequency Table with Amount Category

Amount Category	Cash Withdrawal (3)	Bill Payment (6)	Fund Transfer (7)
1000	321	2	0
1500	113	0	0
2000	805	4	109
2500	127	0	8
5000	10537	100	113
7000	78	0	1
10000	11201	0	11
15000	352	1	6
20000	21901	0	3
25000	1512	8	2
40000	912	0	120
50000	0	0	4
100000	0	0	6

Journal, Advances in Mathematical & Computational Sciences
Vol. 12 No. 2, 2024 Series
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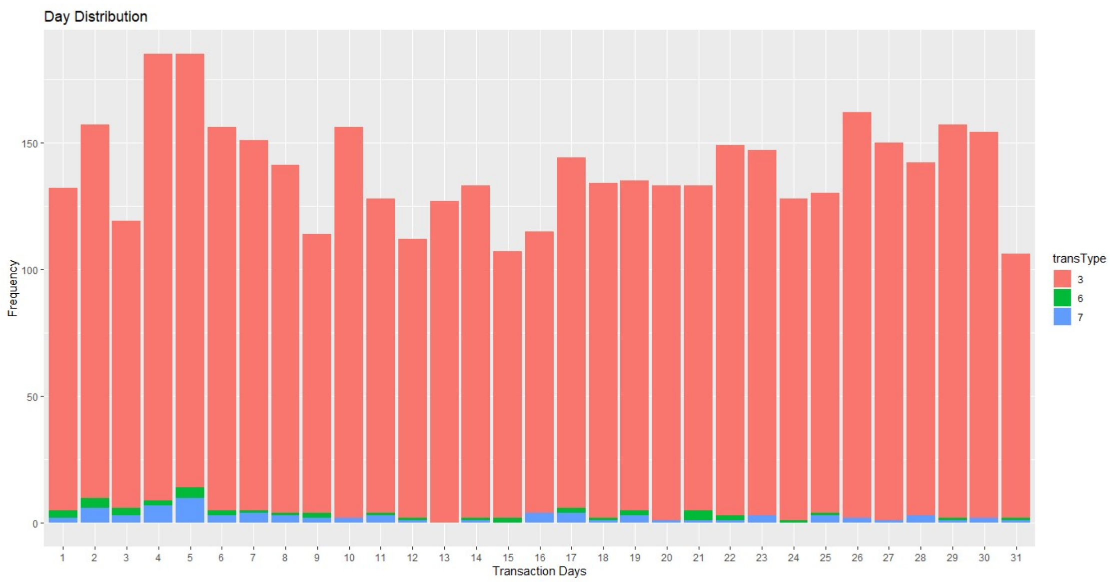

Figure 6. Daily Transaction Distribution with TransType

Table 2. Hourly Visits to ATMs

Hour	Frequency
0	0
1	1,329
2	363
3	351
4	311
5	3,350
6	1,300
7	5,324
8	11,975
9	73,456
10	100,050
11	291,911
12	115,987
13	114,011
14	30,512
15	57,786
16	10,000
17	11,200
18	13,482
19	75,116
20	6,203
21	1,105
22	2,214
23	1,500

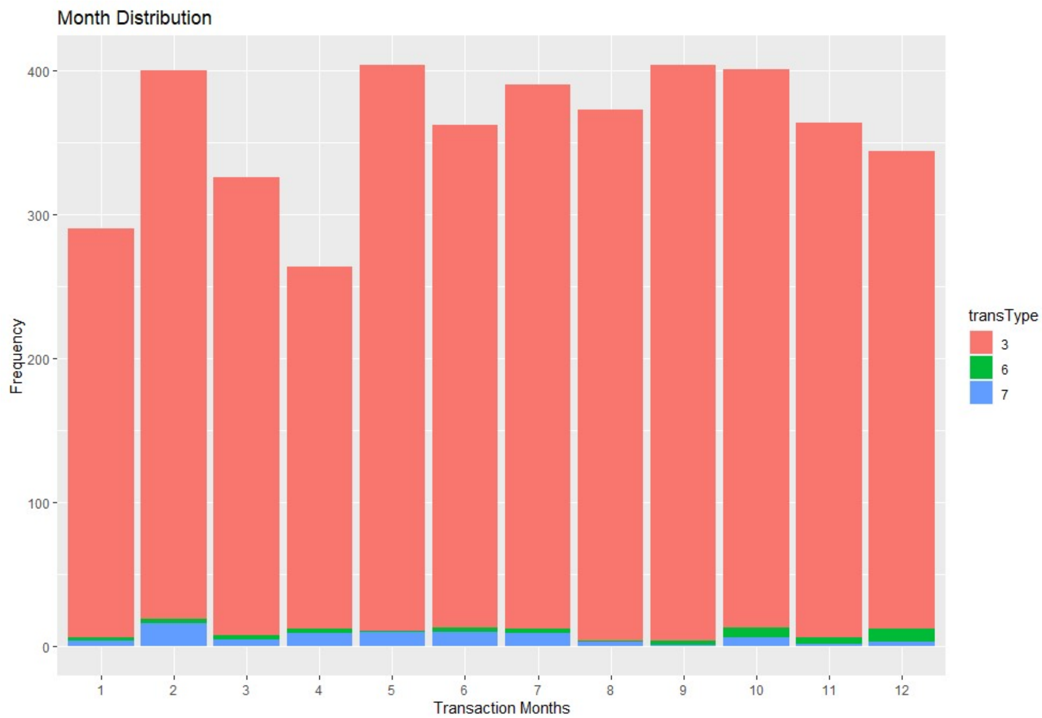

Figure 7. Monthly Transaction Distribution with TransType

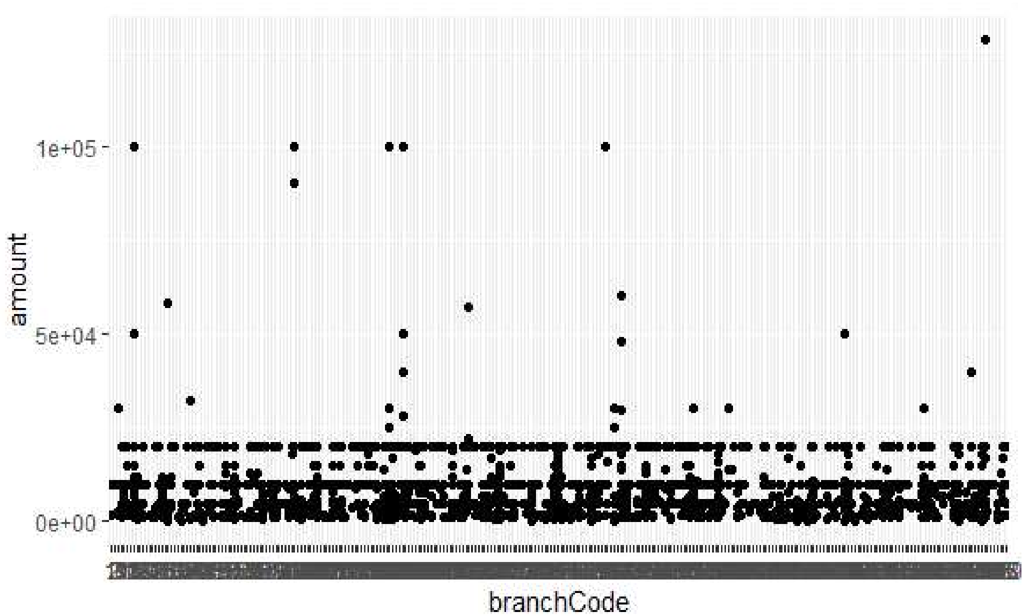

Figure 8. Amount and BranchCode Scatter Plot

2. We identified several patterns in user behavior and preferences through analyses of customer transaction data and device error logs. These patterns include a preference for ATMs located in areas with high visibility and easy access, as well as those with lower failure rates and the capability to dispense high denominations of naira notes. Some patterns in ATM usage observed outside of business hours or in distant proximity to customers raised concerns related to potential fraud. Additionally, transactions involving unusually large amounts of cash were more likely associated with fraudulent activity. These findings underscore the need for banks to implement robust fraud detection and prevention mechanisms, such as real-time transaction monitoring and automated fraud detection systems.
3. During the analysis of device error data, it was observed that the primary causes of transaction failures and ATM downtime are network fluctuations, card reader device failures, PIN pad issues, and shutter or cash jams during cash dispensing. Network fluctuations (65.8%) and card reader failures (18.2%) were found to have the highest occurrence, followed by cash jams (11%) and PIN pad (5%) issues, which collectively accounted for the total ATM downtime
4. We explored opportunities for advertising personalized products and services which could include third party products on ATMs based on user transaction history and preferences. This finding on third party adverts could generate revenues for the Nigerian banks. By personalizing marketing campaigns and product recommendations, banks can provide more targeted and relevant services to their customers. This means users who conducted certain types of transactions, such as frequent international transfers or high-value purchases, were more likely to respond to targeted marketing campaigns for related products and services.

4. CONCLUSION

The study demonstrates the value of analyzing ATM big data for improving banking services and maximizing customer satisfaction. By identifying patterns in ATM usage, detecting potential fraud, and personalizing marketing campaigns, banks can better meet the needs of their customers and stay ahead of the competition. However, further research is needed to explore the full potential of ATM big data, particularly in the areas of machine learning and artificial intelligence. The study has several limitations, including the limited availability and quality of data from some banks, which may have affected the representativeness of our findings. Additionally, our study only focused on ATM big data and did not consider other sources of data, such as point of sales (PoS), online banking transactions and customer feedback, which could provide additional insights into user behavior and preferences. Furthermore, our study did not address the challenges of data privacy and security, which are critical concerns in the use of big data in the banking industry.

Future research could address these limitations by collecting more comprehensive data from multiple sources and using more advanced techniques for data analysis and modeling to build a complete system for ATM big data applications. Additionally, future research could explore the use of machine learning and artificial intelligence to improve fraud detection and prevention, as well as to provide more personalized and targeted services to customers. Finally, future research could also investigate the impact of ATM big data on the overall performance and profitability of banks and financial institutions in Nigeria.

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