The use of Artificial Intelligence in Detecting Mobile Money Fraud In Ghana

Student ID: 64562023

May 14, 2022

Silas Sangmin

Research Methods

– Final Paper

Abstract

Technology is amazing , but it is harmful and dangerous to humanity when it is misused. While some people use technology to make life easier and better for others, others use it for nefarious and self-interested purposes that endanger humanity. A typical scenario is a mobile money transaction service. It is a groundbreaking technology that several institutions around the world have embraced. Life becomes considerably easier with mobile money. On the other hand, Scammers take advantage of the expanding popularity of mobile money to steal money from unsuspecting users. A thorough study of the growing number of mobile money fraud cases reveals a worrying impact on individuals and businesses, particularly small and medium-sized businesses. As a result, this article aims to delve deeper into mobile money fraud and design a lasting solution to this menace using Artificial intelligence.

Table of Contents

Chapter 1 Introduction

Background

In the last two decades, the use of mobile phones has increased worldwide, particularly in developing nations like Ghana. However, access to financial and banking services remains a difficulty for most of the population in these developing countries (Pénicaud & Katakam, 2013). As a result, several mobile network firms now offer mobile money services (Jussila, 2015). Low-income individuals in many countries, particularly in Africa, are increasingly using mobile money services to conduct financial transactions. In Ghana, there were around 31 million mobile users in 2015, with MTN dominating the other networks with 46 percent (National Communications Authority, 2015). A study conducted by PricewaterhouseCoopers found out that 80 percent of Ghanaians are unbanked (2011), thereby using mobile money service as the most convenient means of transacting businesses and transferring money to other people. However, the mobile service system has been under threat because other unscrupulous persons use it to scam subscribers and steal their monies (Chatain et al., 2011).

The number of mobile money service subscribers is increasing due to the rising population of Ghanaians and mobile phone users. In 2014, the mobile money service was GHC11bn with 2.3 million active users; it shot up to GHC31 million in 2015 with 10.4 million active users, and as of July 2016, the estimated value is GHC37.07bn, representing 118 percent growth over the previous year's figures with active users of 17.2 million (Akomea-Frimpong, 2017). It is also the most accessible and convenient means of transacting business for medium and small-scale enterprises. A threat to this system may pose a severe threat to retail businesses in Ghana.

Therefore, leading to slower economic growth and business growth. Small and medium scale businesses in Ghana, Kenya, Cameroon, and many other countries especially developing countries, rely primarily on mobile money network transactions for convenient and fast business deals. Mobile money is a groundbreaking technology that empowers the financial inclusion agenda. It is easily adapted and used by tech-savvy and all classes of people in society. It has brought banking to the level of everyone, including middle- and low-income earners. Unlike the bureaucratic banking system, one can now send or receive money as low as GHC0.50 from a friend, family member, or business partner without passing through the formal and complicated procedures witnessed in the banking sector. All that is needed for a successful transaction is a registered SIM card and a mobile phone device. The good thing is that many e-commerce platforms, including retail and fintech companies, are now integrating it into their payment systems. Before processing payment, customers visiting and buying from these platforms no longer need to possess a credit card like MasterCard or PayPal. Though not proven, many e-commerce purchasers turn away due to prolonged and ambiguous payment systems. But mobile money has come to simplify it, and e-commerce sites like Jumia, Alibaba, and many more are booming because customers can now purchase and process payments with handheld mobile devices.

Problem statement

The rising mobile money fraud cases in Ghana concern all citizens. Selfish and unscrupulous people use the mobile money system to commit dubious crimes by scamming and stealing subscribers' money.

Purpose/Objective

This study aims to examine the trend of mobile money fraud and how the evolving power of Artificial Intelligence can be employed to tackle this menace. According to a study conducted by Razaq et al., these fraudsters keep adapting new and complicated strategies that simple machine learning models might not detect and address (2021). Delving deep into the operations of mobile money and understanding the issue from mobile subscribers' point of view will provide vital information for designing powerful and complex machine learning algorithms that will enable the detection and prediction of potential fraud transactions in the system. The study seeks to discover the threats that mobile money fraud possesses on individuals and the ways of these scammers to enable a design of a lasting solution to this problem.

Brief Theoretical/Conceptual Framework

In this study, two main theoretical frameworks are being explored. One of these is the Fraud triangle/fraud diamond/fraud pentagon (FDT). The second theory is the general deterrence theory (GDT). The later theory will be analyzed in controlling mobile money fraud, while the former theory is used to examine the causes of mobile money fraud. Even though there is no specific theory on mobile money fraud, the fraud triangle theory was first coined by Donald Cressey in 1986 (Cressey, 1986). The theory anchors what causes a person to commit fraud in society as implored by three factors. Thus, opportunity, rationalization, and pressure. Cressey identified that people commit crimes when they need to fulfill a financial need they don't open to people. Still, these people are in positions that allow them to violate rules to obtain money to solve their problems based on their motives (rationalization). According to the FDT, a person involves in fraud activities based on the underlying free factors. A fourth variable called capability was added to the triangle to form the fraud diamond. Many fraudulent transactions would not have occurred without the person with the right capabilities using the variables in the fraud triangle. Marks (2009) expanded the diamond theory to transform it into a fraud pentagon.

The general deterrence theory (GDT) is a framework that will be analyzed to assist with or prevent mobile money fraud. It is considered suitable for controlling mobile money fraud (Akomea-Frimpong et al., 2019, p. 18). This theory examines the countermeasures to prevent fraud by dealing with criminals involved in the act, which serves as a deterrence to other potential fraudsters.

Research Questions

The study seeks to explore mobile money fraud in Ghana. The research examines the following research question:

How effective is artificial intelligence in detecting mobile money fraud in Ghana?

Therefore, the paper will study mobile money fraud causes and patterns to design an artificial intelligence model to detect and prevent fraudulent mobile money transactions. From the main research question, sub-questions are formulated for the study as outlined below:

- What are the causes of mobile money fraud in Ghana?
- How can machine learning Algorithms be implored to address mobile money fraud?
- Which machine learning model can best tackle mobile money fraud in Ghana?
- How concerned are individuals about mobile money fraud in Ghana?
- What is the effect of mobile money fraud on small and medium scale businesses in Ghana?

In addition to answering these questions, the paper will test the following hypotheses.

Null hypothesis: Artificial intelligence is not effective in detecting Mobile money fraud in Ghana.

Alternative hypothesis: Artificial intelligence is very effective and efficient in detecting Mobile money fraud in Ghana.

Nature of the Study (Methodology Overview)

This section outlines the study's suggested methodology and how data will be collected for analysis. The study will employ qualitative research methodology in the form of experimentation.

This technique is based on the concept that fraud issues require more than theoretical research and investigation. It is necessary to take a more practical approach, such as experimenting with machine learning algorithms and artificially intelligent system designs. Other approaches may produce conclusions based on theoretical reasons that are difficult to apply in practice. Questionnaires and surveys will be used to collect data.

Significance of the Study

Mobile money provides an easy and more convenient means of doing money transactions in Ghana. The number of mobile money subscribers keeps growing daily in the country from all sides of the mobile network operators (MTN, Vodafone, Airtel Tigo, etc.). But the attacks on these subscribers are alarming and therefore need considerable attention to ensure the safety of all people in this system. It is also a medium for promoting financial inclusion in developing countries. The system is convenient and accessible to individuals of various income standings, from higher-income earners to lower-income earners. This calls for the need to adopt robust measures and technologies to ensure mobile money safety and business transactions. Hence, this paper is relevant because it seeks to address the loopholes identified in the mobile money system in Ghana.

CHAPTER 2 LITERATURE REVIEW

Review of Theoretical/Conceptual Literature

People commit fraud due to three core factors, pressure, opportunity, and rationalization, as propounded in the fraud triangle theory by Cressey (1886). This framework helps to examine why individuals get involved in mobile money fraud in Ghana. Using the fraud triangle, Akomea-Frimpong et al. explained in their paper that people commit fraud because they may be experiencing financial challenges, which trigger them to think that they can use their acquired skills in a situation to illegal loot money to address their problems. Therefore, this is among the many reasons individuals engage in mobile money fraud in Ghana. The study also discussed other causes of mobile money fraud, such as weak internal control Systems to curb the problem, lack of sophisticated technology to detect and prevent fraud, inadequate education and training of system subscribers, and poor remuneration of employees (2019). Mobile Money Transaction Services is rapidly growing, and there is a need to ensure security in the system. The best approach is to use Machine Learning models such as supervised and unsupervised techniques (Zhdanova et al., 2014).

In dealing with fraud, Botchel et al. proposed an enhanced CBR model to improve the performance of standard CBR systems for fraud identification in Mobile Money transfers (2014). However, according to Razak, fraudsters exploit the lack of awareness among the technologically excluded and constantly update their scam approaches. They explained that victims refuse to report due to a lack of trust in authorities. Women fear to report due to fear of maltreatment and embracement (2021). As these perpetrators continue to enhance and advance their cunning strategies, it becomes daunting to deploy technological tools and machine learning models to help curb this challenge. Even though tech giants have not completely turned away from attempting to defeat fraud in past decades, there have not been any effective working software programs that can boast of detecting and controlling fraud transactions in the mobile money system. However, Tengeh & Gahapa Talom claim that Mobile Money is a plausible solution to financial constraints that hold back the development of SMEs. They also cited that some SMEs use mobile money for security, accessibility, and convenience (2020). It, therefore, means that any threat to the system could lead to these businesses withdrawing the services and payments channels from the mobile system to other alternatives that might prove to be more secure and less prone to fraudulent activities.

Ackah also conducted a study to determine the impact of mobile money services on the growth of SMEs in the Tarkwa municipality in the Ashanti region of Ghana. It was concluded that mobile money has no significant impact on the business operations of SMEs within the Tarkwa municipality (2016). The finding from the research indicates that fraud may not pose any significant effect on SMEs in Ghana since it may be the case that mobile money does not affect business operations. This propels further studies to affirm the conclusion from Ackah's research. For instance, many businesses, even the banking sector, are integrating mobile money services into their financial models. Hence it piques researchers' interest to hear mobile money has no significant impact on SMEs in Ghana, and part of the aims of this paper is to investigate the impact of mobile fraud on these SMEs in Ghana. According to Andoh et al., although several variables affect the growth of SMEs, accounting fraud is the dominant and the most significant variable which negatively affects the development of SMEs in Ghana (2018).

Review of Empirical Literature

The issue of mobile money fraud has gained significant concern in the field of machine learning, and several empirical studies have been conducted on the area. Bochey et al. paper demonstrated an ability to predict the causes of fraud in mobile for imbalanced data using linear regression (2020). However, as indicated earlier, the ways of the fraudsters are getting unpredictable and very complicated that any simple linear regression cannot accurately be adapted to control fraud in the mobile money sector. This has led to further experiment done by Mohamed et al., who designed a machine learning fraud detection system to identify any fraudulent activities and create alarms based on the predefined and threshold setting rules using a neural network. The study has revealed a suitable parameter and proven that neural networks can predict potential and non-potential fraud cases. After performing several experiments, the average accuracy of the model was more than 90% . Moreover, Botchey et al.'s experiments demonstrated an Artificial Intelligent model using the ensemble method, which showed that gradient boosted decision trees can adequately predict fraudulent transactions in mobile money transfer services. Also, Bernoulli Naïve Bayes perform well in their experiment (2020). In their paper, Rojas et al. explored a synthetic dataset like real-world mobile money data for simulation of mobile money fraud detection models. It will also help financial companies generate consistent data for testing their fraud detection models (2018). The rationale behind the synthetic simulation model stems from the fact that there is no well-defined and appropriately formatted data for mobile money transactions, which makes it tedious and hectic for Artificial Intelligence engineers who seek to explore this area.

This leads to the production of inefficient models because of poor training due to inconsistent data or a lack of required data for training machine learning models. The implication of the synthetic model is the provision of safe and efficient data for simulating intelligent models by future Artificial Intelligent explorers. Access to secure data implies the delivery of efficient models in the future. Another research was conducted by Kang (2019) in an attempt to design a machine learning solution for mobile money fraud detection. He used a supervised approach with a decision tree and a random forest model using paySim dataset from Kaggle. According to the F-scores he obtained, both models achieved good accuracy, with the enhanced tree performing somewhat better. The accuracies are higher than expected, and he believed that part of the cause is due to the dataset's synthetic nature.

Synthesis of Literature Findings

A general review of various studies conducted by several scholars indicates an alarming growth rate of fraud nuisances in developing countries, and trimming it down to Ghana yields no different concerns. Technology is one of the main tools used to make human lives more convenient and comfortable. On the other side, technology is a two-edged sword. Its misuse is detrimental and a threat to humans. In the global atmosphere, there exist different caliber of individuals. While others thrive for the good of the universe, others dwell at the expense of the world. Thus, their lives turn into a threat to humankind. This explains why people commit various crimes in society, for which mobile money is not an exception. Perhaps, due to Cressey's crime theory of why people commit crimes in the community. The cause of mobile fraud stems from ignorance on mobile subscribers' side, weak technology tools to detect scams, and lackadaisical attitude of service agents such as the leading mobile network companies like MTN, Tigo, Vodafone, and Artel Gh towards the act. The fraud diamond is also another contributing factor to mobile money fraud.

Despite the efforts by researchers to find a lasting solution to the problem of mobile money fraud, there have not been any significant headways due to inadequate data to fully grasp the root causes of the underlying fraud trend and to train and deploy powerful models into the system to deal with fraud. Powerful machine learning algorithms and models have been widely used in tackling pressing world needs in medicine in diagnosing diseases and manufacturing industries for performing tasks that humans had had to do manually. The entertainment and movie industry implored it for movie recommendation systems, video editing, agriculture, and even the traditional banking and financial sector to detect spam credit card messages or encrypt transaction details. But its adoption and usage in mobile money operations seem slow. However, increasing forces to digital payment, such as the mobile money system, is a powerful component that drives development and growth. Therefore, it behooves experts to implore creativity and intuitive strategies that will yield practical knowledge in designing solutions to this problem of mobile money fraud. There is no working model, not even a less effective machine learning model geared towards curbing the rising number of fraud cases even though there were attempted and failed models.

This suggests a compelling caveat that researchers need to identify and solve, which is among the reasons for this study. This paper seeks to identify the underlying causes of ineffective mobile fraud detection tools to correct them and fill those potholes in the reviewed research and experiments studied during the literature review of this paper. Another gap to be filled is that researchers approach the issue of mobile money fraud in a general and more theoretical manner. However, this area of study should be tackled practically through experimentation with machine learning algorithms. It does not auger well to handle this area with only theories about the cause and effect variables but must be more empirical and realistic.

CHAPTER 3 METHODOLOGY

This section discusses the proposed methodology of the study and how data will be obtained for examination. Quantitative research methodology in the form of experimentation will be used for the study. This approach is informed by the idea that fraud issues need more than theoretical studies and exploration. A more practical approach like experimenting with machine learning algorithms and Artificial intelligent system designs is necessary. Using other methodologies could result in conclusions based on theoretical explanations and may be very hard to apply practically. The methods for this project will be mainly on implementation in Python. But data is essential for the implementation. By collecting the data, powerful machine learning models can be designed to detect fraud patterns and prevent them. However, as the use artificial intelligence grows, the demand for a large amount for data increase. These models can only perform better when trained with millions to billions of data. Due to various factors, such as ethical constraints, privacy concerns, and government or company laws, obtaining transaction data from mobile money companies or agents can be challenging. Furthermore, suppose such data is made available. It may be in minimal quantities, missing information on confirmed fraud cases, or only carrying a limited amount of information.

As a result, the proposed methodology uses a dataset from Kaggle that combines the behavior and habits of multiple users in a mobile environment. This will be ideal for the task ahead and will be used to train a machine learning model. Apart from using the dataset from Kaggle, data will be gathered using questionnaires and surveys, which will be used to analyze the trend of mobile money fraud in Ghana. The survey will also give an overview and in-depth knowledge of the problem at stake. The creation of a synthetic mobile money transfer dataset is an important step. A supplementary dataset is required due to the lack of a real Mobile Money transaction dataset.

Adnan used hypothetical and fictitious data generated by simulation tools that generate data at random to develop fraud detection models to avoid the hurdles of gathering data (2011). There are many ways to generate data for building Artificial Intelligence models. The suggested system would be built and developed using PyTorch and Fast Ai, which are Python frameworks for developing Machine Learning Models. Data will be classified in the transaction dataset into contexts and then properly to capture fraud behavior as part of preprocessing on the dataset.

Study population and sampling

The target population for this paper is the Ghanaian population. The sample will be drawn from this population using a stratified sampling technique. Stratified sampling divides the population into subpopulations with significant differences. It allows for drawing more precise conclusions by ensuring that each subgroup in the sample is appropriately represented. With a stratified sampling approach, the population will be divided into subgroups based on the relevant attribute. These subgroups are the mobile money agents, mobile money subscribers, mobile money firms, fraud victims, and the like. Then computes how many people should be sampled from each category based on the population's overall proportions. And then select a sample from each subgroup using random or systematic selection. A stratified sampling technique will ensure that no single subgroup dominates the other subgroups in the sample for the research survey ("Sampling methods | Types and techniques explained," 2021).

Data Collection

Survey questions will be distributed to the research participants. This will be sent via survey monkey, an online software that enables effective and efficient data collection using surveys. The participants will be chosen based on their responsibilities in Ghana's mobile money business and their contributions to the fight against mobile money fraud. Thus, they will include people from diverse roles in the Ghanaian mobile money sector, such as mobile money agents, mobile money subscribers, and regulators of the mobile money system. The regulators of the mobile money system are the telecommunication firms such as MTN, Airtel Tigo, and Vodafone. Their personnel, as well as their agents or merchants, will be surveyed. Banks will also be studied as the third indirect participant of the mobile money system.

Instrumentation and Data Analysis

After gathering the relevant data for the study, the next stage involves processing and analysis. Python programming language will help prepare and process the data. It has inbuilt libraries and frameworks such as pandas, NumPy, Matplotlib, and other statistical libraries. The gathered data from the survey will be analyzed to find patterns of mobile money fraud in Ghana. As part of the research objectives, statistical tests will be performed to answer the research questions and to validate or test the research hypothesis. The analysis will also include visualization and bivariate univariate analysis of the data variables. A correlation test would be used in performing the statistical test from the surveyed data. Thus, for quantitative variables such as transactions of incomes, the number of fraudulent transactions, and the time these transactions mostly occur. The other dataset from Kaggle is what will be used to build and train the machine learning model with the PyTorch and fast ai. But first and foremost, preprocessing will be done by getting rid of unwanted variables, transforming them to suit the model parameters, and removing missing cells. Python is Good for this task as well. The machine learning model will employ a deep neural network in a supervised manner. Performance of the model will be measured, and evaluation will be based on F-scores and general accuracy percentage.

Limitations and Delimitations

Some limitations of this research are the low participation rate due to smartphone accessibility by research participants. It is expected that most of these participants will possess smartphones or devices. However, it may occur that these people do not have these devices to respond to the survey questions as speculated. For instance, some mobile money subscribers use the popularly known non-smartphones called 'yam' in Ghana, hence can not respond with these devices. Notwithstanding, the research adopts a quantitative approach that will enable the collection of a large sample to present a true reflection of the population. Also, the stratified sampling technique will prevent bias and unfair selection of research participants. This affirms both the internal and external validity of the paper.

Ethical Considerations

Participants who accept privacy terms will receive survey questions before the data collection. The privacy terms will outline that the data collected will be treated with high integrity and their privacy assured. Data will be safe on an online drive with a secure password. Research participants will be highlighted on the purpose of the research and why the data is collected to ensure confidentiality. These ethical standards cover topics including honesty, informed permission, data anonymization and storage, participant access to data, and the duty of secrecy for all researchers.

Conclusion

The literature review found that some of the causes of mobile money fraud are weak internal control systems, poor salaries of mobile money operators/merchants, ignorance on the side of mobile money subscribers, and inadequate technology to help detect fraud cases. This paper explores two main fraud theories in mobile money transactions in Ghana. These frameworks are the fraud triangle theory, which further evolves to fraud diamond, then pentagon theory. It is used here to analyze why people may engage in mobile money fraud. The second theory is the General deterrence theory explored in the paper as a suitable fraud prevention mechanism. Findings from the literature review indicate a lack of working Artificial intelligence or machine learning models to detect and prevent mobile money fraud. Therefore, this paper will examine the problem to enable the design of a fully functioning machine learning agent that will effectively curb fraud in Ghana's mobile money sector.

Moreover, as part of the objectives of this research to examine the best approach to tackling mobile money fraud, machine learning algorithms have been designed and simulated by technology enthusiasts in other countries. The performance evaluations of the algorithms prove promising and artificial intelligence could be the way. However, the gap identified is that the evaluations were mainly on simulations and lacked empirical demonstrations, and this paper tackles the problem more empirically to design an artificial intelligent-aided model using a neural network to detect fraud and prevent it in Ghana.

References

Adedoyin, A., Kapetanakis, S., Samakovitis, G., & Petridis, M. (2017). Predicting fraud in mobile money transfer using case-based reasoning. *Artificial Intelligence XXXIV*, 325-337. https://doi.org/10.1007/978-3-319-71078-5_28

Adnan, M. A. (2011). Detect CNP Fraudulent Transactions. *World of Computer Science and Information Technology Journal*, 8(1)

Akomea-Frimpong, I., Andoh, C., Akomea-Frimpong, A., & Dwomoh-Okudzeto, Y. (2019). Control of fraud on mobile money services in Ghana: An exploratory study. *Journal of Money Laundering Control*, *22*(2), 300-317. https://doi.org/10.1108/jmlc-03-2018-0023

Andoh, C., Quaye, D., & Akomea-Frimpong, I. (2018). Impact of fraud on Ghanaian SMEs and coping mechanisms. *Journal of Financial Crime*, *25*(2), 400-418. https://doi.org/10.1108/jfc-05-2017-0050

Asomanin Anaman, K., & Bernice Nyadzi, W. (2015). Analysis of improper disposal of solid wastes in a low-income area of Accra, Ghana. *Applied Economics and Finance*, *2*(1). https://doi.org/10.11114/aef.v2i1.633

Botchey, F. E., Qin, Z., & Hughes-Lartey, K. (2020). Mobile money fraud prediction—A cross-case analysis on the efficiency of support vector machines, gradient boosted decision trees, and naive Bayes algorithms. *Information*, *11*(8), 383. https://doi.org/10.3390/info11080383

Botchey, F. E., Qin, Z., Hughes-Lartey, K., & Ampomah, E. K. (2022). Predicting fraud in mobile money transactions using machine learning: The effects of sampling techniques on the Imbalanced dataset. *Informatica*, *45*(7). https://doi.org/10.31449/inf.v45i7.3179

Chatain, P.L., Zerzan, A., Noor, W., Dannaoui, N. & De Koker, L. (2011).Protecting Mobile Money against Financial Crimes: Global Policy Challenges and Solutions, World Bank Publications, New York, NY.

Drucker, P. F. (2017). Managing oneself. *Leadership Perspectives*, 315-324. https://doi.org/10.4324/9781315250601-24

Jussila, A. (2015). Mobile money as an enabler for entrepreneurship: case Eastern Africa. (Master's Dissertation, Aalto University). Retrieved from http://epub.lib.aalto.fi/fi/ethesis/pdf/13925/hse_ethesis_13925.pdf

Kang, H. (2019). Fraud Detection in Mobile Money Transactions Using Machine Learning. Iowa State University, 8(1)

Marks, J. (2009). Playing Offense in A High-Risk Environment, Crowe Horwath, New York, NY.

Mohamed, A., Bandi, A. F., Tamrin, A. R., Jaafar, M. D., Hasan, S., & Jusof, F. (2009). Telecommunication fraud prediction using Backpropagation neural network. *2009 International Conference of Soft Computing and Pattern Recognition*. https://doi.org/10.1109/socpar.2009.60

National Communications Authority (2015), retrieved from:

www.nca.org.gh/assets/Uploads/Telecom?Voice-Subscription-Jan.-to-Dec.-2015.pdf

Pénicaud, C., & Katakam, A. (2013). State of the industry 2013: mobile financial services for the unbanked. GSMA. Retrieved from http://www.gsma.com/mobilefordevelopment/wpcontent/uploads/2014 /02/SOTIR_2013. pdf

PricewaterhouseCoopers (2011), retrieved from: www.pwc.com/gh/en/pdf/ghana-banking-survey-

2011.pdf (accessed 11 October 2017).

Quansah, F., Rosemary Ankoma-Sey, V., & Aframea Dankyi, L. (2020). Determinants of female students' choice of STEM programmes in tertiary education: Evidence from senior high schools in Ghana. *American Journal of Education and Learning*, *5*(1), 50-61. https://doi.org/10.20448/804.5.1.50.61

Razaq, L., Ahmad, T., Ibtasam, S., Ramzan, U., & Mare, S. (2021). "We even borrowed money from our neighbor". *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW1), 1-30. https://doi.org/10.1145/3449115

Rojas, E. A., Axelsson, S., & Baca, D. (2018). Analysis of fraud controls using the PaySim financial simulator. *International Journal of Simulation and Process Modelling*, *13*(4), 377. https://doi.org/10.1504/ijspm.2018.093756

Sampling methods | Types and techniques explained. (2021, April 23). Scribbr. https://www.scribbr.com/methodology/sampling-methods/

Tengeh, R. K., & Gahapa Talom, F. S. (2020). Mobile money as a sustainable alternative for SMEs in less developed financial markets. *Journal of Open Innovation: Technology, Market, and Complexity*, *6*(4), 163. https://doi.org/10.3390/joitmc6040163

Zhdanova, M., Repp, J., Rieke, R., Gaber, C., & Hemery, B. (2014). No Smurfs: Revealing fraud chains in mobile money transfers. *2014 Ninth International Conference on Availability, Reliability and Security*. https://doi.org/10.1109/ares.2014.10