Factors Influence Customer Satisfaction of International Remittances / International Money Transfers Services Using Ensemble Machine Learning

MSc Research Project
Financial Technology

Abeen Pulikkottil Thambi
Student ID: x21224714

School of Computing
National College of Ireland

Supervisor: Victor del Rosal

National College of Ireland

MSc Project Submission Sheet

School of Computing

Student Name:	……..Abeen Pulikkottil Thambi………………………………………………………………
Student ID:	…………………x21224714…………………………………………………………………….
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Abeen Pulikkottil Thambi
x21224714

ABSTRACT

Remittances are essential financial outflows that overseas workers, students, and immigrants pay back to their home countries, and they have a significant impact on the receivers' welfare. If we wish to improve financial services, it is crucial to understand the factors influencing remittance satisfaction. This study uses a large dataset that contains socioeconomic and demographic information of beneficiaries to create precise forecasting models. The study carefully assesses and compares various classification schemes to find which is the most effective. The classification of remittance satisfaction is studied in this research using machine learning algorithms and bagging techniques including Random Forest, Decision tree, and Gradient Boost. The paper proposes an enhanced comparison across various sentiments and feelings of customer usage of the various remittance applications and discusses the hyper kernel extraction of satisfactory results via RF, DT and GB. A vivid discussion of results and discussion is also shown below.

The results have significant ramifications for financial institutions and service providers, allowing them to improve services and better cater to the requirements of remittance beneficiaries.

Keywords: Remittances, Ireland, Transfers, Satisfaction

1. INTRODUCTION

1.1 Background to the Study

Remittances, or money sent to developing nations by migrants who work abroad, have increased considerably in recent years, rising from $3.3 billion in 1975 to $289.4 billion in 2007 [1]. In terms of actual amounts and as a percentage of GDP, they now account for approximately twice as much funding as government aid received by poor nations, trailing only foreign direct investment (FDI). An increasing number of papers have examined the development impact on remittances with different dimensions, by poverty, inequality, growth, education, infant mortality, and entrepreneurship, as researchers which grown aware of the rising range and constant nature of remittances to emerging countries [2]. The subject of how remittances use money transfer applications to increase customer involvement in remittance-recipient countries has received surprisingly little attention, though. The argument that beneficiaries of remittances will assist amplify their impact on development makes this topic pertinent as well [3].

Remittances are financial transfers that people make when they return home from working abroad. These funds are typically provided in order to support family members, pay for necessities, or finance businesses and educational endeavours. Remittances are a major contributor to global economies since they promote consumer participation and benefit both individuals and companies. This paper will discuss the significance of remittances, their impact on customer involvement, and how organizations can benefit from this income flow [4]. Remittances have grown dramatically over time and have become an important part of the global economy. According to the World Bank, remittances to nations with low or moderate incomes reached an all-time high of $551 billion in 2019. This significant influx of cash stabilizes economies and households, reducing poverty rates and fostering growth [5].

One significant aspect of remittances is the impact on consumer interaction. For the individuals and families who receive remittances, they serve as a lifeline, increasing their standard of living and overall wellbeing. Remittances can be used to cover basic needs like housing, healthcare, food, and education. By supporting these key components, remittances promote consumer fulfilment and engagement because they immediately contribute to the welfare and expansion of the recipient's family [6].

If companies are aware of the needs of their customers and create products and services to satisfy those needs, remittances can aid in corporate growth. By recognizing the importance of remittances in their everyday lives, businesses can develop plans. For instance, financial institutions can offer specialized remittance services including affordable transfer possibilities, usable withdrawal procedures, or cutting-edge mobile banking solutions. By doing this, companies increase customer loyalty and engagement and establish themselves as facilitators of the financial security of remittance receivers. Remittance data can also be used by businesses to discover vital information about consumer behavior and preferences. By looking at transaction patterns, spending patterns, and cash flows, businesses can identify emerging market trends, consumer preferences, and potential growth opportunities. Using this data-driven methodology, businesses can develop tailored product offerings, targeted marketing campaigns, and customized customer experiences [7].

Generally speaking, cash remittances are essential to bank operations because they are a significant source of revenue and promote client interaction. Remittances play a big role in the stability and overall financial health of banks since they entail the transfer of money from people living or working abroad back to their home nations. The ability of banks to make money through cash remittances is one of the main factors in their importance. Fees and commissions levied on remittance transactions are how banks make money. These charges could be for service fees, transfer fees, or charges for the conversion of foreign currencies. Banks that receive a lot of cash remittances through their systems can build up sizable revenue streams that they can utilize to pay for operational costs, make investments in infrastructure and technology, and guarantee the long-term viability of their services [8].

This paper focuses on realizing the value of using remittance data to explore and comprehend its significance in the modern world and how businesses require it to build a much larger cash ecosystem. As a result, in addition to the mitigating element, an artificial intelligence system is needed to comprehend cash remittance services and how the customer thinks about them. For improving the current services further, this analytical insight is essential. Python will be used in the paper's simulations together with machine learning.

1.2 Statement of Research Problem

The study aims to address the following research problem on the key factors which influence customer satisfaction in the context of international remittances or international money transfer services.

1.3 Research Objectives

1. To identify the factors that have a significant impact on customer satisfaction within the realm of international remittances or money transfer services.

2.To analyze the effectiveness of various classification schemes and machine learning algorithms, such as Random Forest, Decision tree, and Gradient Boost, in predicting and understanding remittance satisfaction.

3.To assess the potential implications and applications of the research findings for financial institutions and service providers to enhance their services and cater more effectively to the needs of remittance beneficiaries.

1.4 Research Question

What factors influence customer satisfaction of international remittances / international money transfers services?

1.5 Research Hypothesis

The level of customer satisfaction in international remittances or international money transfer services is influenced by a combination of socio-economic factors, service quality, ease of use, accessibility, and tailored offerings.

1.6 Significance of the Study

This research provides to the existing literature by giving insights into the specific factors which impact customer satisfaction within the domain of international remittances. It evaluates the efficacy of machine learning algorithms in understanding and predicting satisfaction patterns. In addition, with, financial institutions and service providers can identify the findings to enhance their services and also customer oriented offerings. It is also important that marketing strategies and product remittance data can be developed. Aside from that the reduction in poverty , enhanced quality of life and economic development in beneficiary nations.

2. LITERATURE REVIEW

Third-party payment (TPP) systems, which are non-financial organisations that provide services related to payments by linking organisations with banks through technology, are part of the banking and finance technology (Fintech) industry. These systems rely on big data, cloud computing, and mobile internet technology. They are classified as monetary agent organisations that collaborate with big banks to provide third-party payment solutions [31]. Both formal and unauthorised remittances have an influence on the banking industry's development. Money transfers, when conducted throughout formal channels, can lead to recipients opening financial accounts and acquiring knowledge about bank lending services. Private investments and economic expansion are linked to financial growth. Financial service providers contribute to growth and development by assisting lucrative enterprises. The historical significance of the banking system in facilitating capital mobilisation for industrialisation has been emphasized .

2.1 TPP Platform

One of the fundamental components of the financial technology (Fintech) sector is third-party payment (TPP) [31, 32, 33]. TPP platforms are independent, non-financial companies that offer payment services connecting the bank payments and settlements systems of businesses and commercial banks, as described by [34]. The TPP platforms share the commonality of relying on big data, cloud computing, mobile internet, and other developing technologies to survive as the primary financial form of Fintech, which is the term for technologically enabled innovation in financial services [35]. Third-party independent institutions that have agreements with major banks, the ability, and a good reputation provide third-party payment systems [36]. These organisations fall under the category of service agent organisations with a distinct payment duty.

2.2 Remittance with TPP Platform

Remittances are sent through both official and unauthorized channels, as evidenced by the literature [9]. According to [10, 11], remittances that are routed through official channels have an impact on the financial sector's expansion. Particularly when the recipients of these funds create accounts with commercial banks, this happens. Additionally, when recipients go to the banks, they can learn more about available bank loan products that they could use. We anticipate greater financial development if this effect on the financial industry is significant. However, as the literature has demonstrated [12, 13, 14, 15], financial development is also connected to private investment and economic growth. [16] demonstrated the significance of the services offered by financial intermediaries for creativity and growth. By finding and supporting profitable projects, Schumpeter also shown how financial institutions may promote innovation and growth.

2.3 Growth and Improvement of Remittance with Online Banking

The similar point of view was expressed by [17], who demonstrated the crucial historical role the financial system had in igniting industrialization in England by enabling the mobilization of capital for "immense works."

Remittances typically have a lower marginal impact on growth in areas with higher levels of financial development, according to additional research [11]. This is since financial development as we currently understand it tends to be linked to the generation of ideas about high investments with the capital, the observation of businesses and the working of corporate governance, trading, risk diversification, and management, mobilizing savings, and facilitating the trading of goods and services. These financial activities typically have an impact on investment and saving choices, technical advancements, and growth in the economy [14].

On the other hand, there is also evidence in the literature for a counterproductive pathway between remittances and growth. First, remittances take place in an environment of information asymmetry, where the sender lacks control over how the recipient uses the transferred funds. As a result, the recipients may not use the transferred funds for investments or as productively as intended. This is according to proponents of the negative impact of remittances on growth. Second, because remittances are typically given to families for consumption smoothing rather than investment, recipients may mistakenly believe that they are receiving additional income from the remitted funds and increasing their time spent relaxing, which is likely to have a detrimental impact on labor productivity and growth [18, 19, 20].

3. DATA AND METHODOLOGY

3.1 DATA

The data used in this paper has been collected through snowball sampling for 75 total respondents with over 15 questions. In the study method known as snowball sampling, first participants who satisfy specific criteria, and they are asked to recommend more volunteers who meet the same criteria. The sample size is increased while this procedure keeps on in a chain-like fashion. When studying elusive or marginalized communities and conventional sample techniques are not feasible, it is frequently used.

While the questions have been carefully formulated to understand the gist of whether users are satisfied with the usage of third-party apps for remittances for money transfer. Since international students use third-party applications to send it back to their homes, 70% of the respondents are students and nurses.

The questionnaires are quite detailed and has very intricately focused on understanding certain nuances about the nature of remittances. The following showcases the general questionnaires.

Table 1 Questions and Options

S. No	Question	Options
1	What is your profession?	1) Teacher 2) Doctor 3) Nurse 4) Soliciter 5) Others
2	Which of the international money transfer app you use?	1) Wise 2) Revolut 3) Remitly 4) OFX 5) Western Union 6) Others
3	How much do you pay for international transaction using 3rd party application?	1) 20% 2) 40% 3) 50% 4) 50%+ 5) Others
4	How much money do you transfer internationally per month (in Euros).	
5	How would you rate the customer support provided by the app's team for any queries or issues you encountered during international transfers?	1) 1 (Worst) 2) 2 3) 3 4) 4 5) 5 (Best)

6	How satisfied are you with the cost/fees associated with international remittance or money transfer services you have used?	1) Very Satisfied 2) Satisfied 3) Neutral 4) Dissatisfied 5) Very Dissatisfied
7	How satisfied are you with the app's transaction speed for international transfers?	1) 1 (Worst) 2) 2 3) 3 4) 4 5) 5 (Best)
8	How often do you experience any technical issues or glitches while making the international transfers?	1) Very Often 2) Never
9	Which of the following option do you trust the most?	1) Banks 2) Third party remittance application

These questions provide a basic idea about understanding if users are indeed satisfied with their usage of third-party apps, majorly asked in the 2nd questions.

3.2 Methodology

Proposed Idea-

The paper proposes a CRISP-DM architecture to formalize a comparative machine learning and Exploratory data analysis study on the symmetrical or asymmetrical nature of customer using remittance applications. It compares across 9 different applications via 15 question and from an audience base of 75 users. The paper showcases visualization results and comparative tables to discuss the essential findings.

CRISP-DM –

For data mining and predictive analytics projects, the CRISP-DM (Cross-Industry Standard Process for Data Mining) methodology is frequently utilised. Let's use the CRISP-DM process to predict customer satisfaction for international residents of Ireland who use third-party remittance apps to send money using a variety of bagging techniques (XGBoost and gradient boost) and conventional machine learning techniques (logistic regression, KNN, and SVC).

1. Business Understanding:
   - Understand the level of customer satisfaction and technical hickups with the application at stake
   - Identify the major factors that influence customer satisfaction such as security, productivity, speed, charges and other macro economic factors or boundaries.
2. Data Understanding:
   - To comprehend consumer feedback, transaction history, app usage trends, and demographic data, the data sources have been examined.
   - Identify data quality issues and missing values that need to be addressed.
3. Data Preparation:
   - Cleanse and preprocess the data to handle missing values and outliers.
   - Feature engineering: Create relevant features such as customer behavior metrics, transaction frequency, and app usage patterns.
4. Modeling:
   - Split the data into training and testing sets for model evaluation.
   - The paper uses a 80:20 ratio to enhance and interpret the results.
   - Apply the selected machine learning algorithms: XGBoost, gradient boost, random forest.
5. Evaluation:
   - Evaluate the models using appropriate performance metrics like accuracy, precision, recall, and F1-score.
6. Deployment:
   - Select the best-performing model(s) based on evaluation results.
7. Monitoring and Maintenance:
   - Continuously monitor the model's performance .
   - Retrain the model by timimg with updated data to maintain its predictive accuracy, precision, recall, F1 Score, sensitivity and specificity.

Domain experts and stakeholders must be included at every stage of the CRISP-DM process to make sure the model is in line with business goals and offers insightful data that will improve consumer satisfaction with the use of third-party remittance apps in Ireland.

3.3 Modelling

All the ML architectures are trained over the same training testing set up of 60 training and 15 testing's, with the same seed value and environmental distribution, to ensure unbiased scoring and testing mechanism. The proposition incorporates 15 fold cross validation for enhancing and distinguishing the deviation and data distribution for each model.

1. **Bagging Architectures.**

   The ensemble learning method known as bagging, or Bootstrap Aggregating, is used to enhance the efficiency and sturdiness of machine learning models. A base model, such as a decision tree, neural network, or support vector machine, is duplicated, and each copy is trained using a different bootstrap sample from the initial training set.

   Voting (for classification) or averaging (for regression) are used in the bagging process to combine the results from each model. In comparison to a single model, the aggregated predictions are typically more accurate and less prone to overfitting. Bagging can better handle noisy data and reduce variation [21]. Due to the independence of each model's training, it also permits parallel processing and Random Forest is one of the most popular algorithm.

   In order to forecast the degree of remittance satisfaction, Random Forest, a potentensemble learning technique, is applied. Multiple decision trees are built throughout the training phase, and their predictions are then combined to provide the final classification [22].

   The algorithm makes use of numerous remittance transaction data, recipient demographics, and other pertinent aspects to categorise recipients' happiness with their remittances. Each decision tree in the Random Forest is trained using a random subset of features on a bootstrap sample of the original data. Random Forest is a reliable option for forecasting remittance satisfaction because it can handle complex interactions in the data, provides feature importance rankings, and is less sensitive to outliers or noise [23].

2. **Boosting Architectures**

   Boosting is a training cycle-based ensemble methodology. It focuses on deep and generic training of an individual model to enhance the performance and determine a training loss curve. It builds many models in a sequential order to improve the performance. In contrast to bagging, which trains base models individually, boosting focuses on iteratively fixing mistakes generated by prior models. AdaBoost (Adaptive Boosting), one of the well-known boosting algorithms, gives instances that were incorrectly categorised more weights and educates succeeding models [24, 25].

On other hand, Extreme Gradient Boosting, or XGBoost, is a potent machine learning technique that is frequently used for classification problems like remittance satisfaction prediction. It is an improved variation of gradient boosting that quickly constructs several decision trees to produce reliable forecasts. XGBoost uses numerous variables associated with remittance transactions, recipient demographics, and other pertinent factors for remittance satisfaction classification. It creates decision trees repeatedly, with each tree focusing on fixing the flaws in the preceding one to produce a highly accurate ensemble model. Regularisation techniques are used by XGBoost to manage overfitting. Moreover, XGBoost is a well-liked option for precise and effective remittance satisfaction prediction. On the other hand, a potent machine learning approach called gradient boosting is employed for classification problems like remittance satisfaction prediction.

Gradient Boosting uses a variety of remittance transaction parameters, recipient demographics, and other pertinent factors to classify remittance satisfaction. Each decision tree is built with the intention of minimising classification mistakes during training, and the final prediction is generated by merging the findings from all the trees. It works well for learning from high-dimensional data. The algorithm is a preferred option for precise and trustworthy remittance satisfaction prediction because of its capacity to learn from errors and adjust to the subtleties of the data [26, 27, 28].

3. Traditional Machine Learning

Traditional ML architectures allow us to compute statistical surveys of how various mathematical models demonstrate the essential metaheuristic covariance distribution enhanced via genomic distribution of features using firefly, and Grey wolf optimization.

The paper also utilizes:

A. **Logistic Regression (LR)**: Logistic Regression works on the distribution of linear features across the scope of the dataset. Enabling features to be mapped via linear relationship with the dependent variable. To anticipate the level of remittance satisfaction, one can utilise logistic regression, a statistical method that is frequently used for binary classification tasks. The binary result, which represents whether remittance receivers are satisfied or not, would serve as the dependent variable in this situation. The independent variables (features) could consist of a variety of remittance-related elements, such as the quantity, regularity, or form of remittance transfers, socioeconomic traits of the receivers, and their opinions on the overall remittance experience.

These input features are merged linearly during logistic regression, and the logistic function is then used to transform the continuous output into a probability score. Each observation is categorised as satisfied or unsatisfied based on a comparison of the anticipated probability to a threshold (often 0.5).

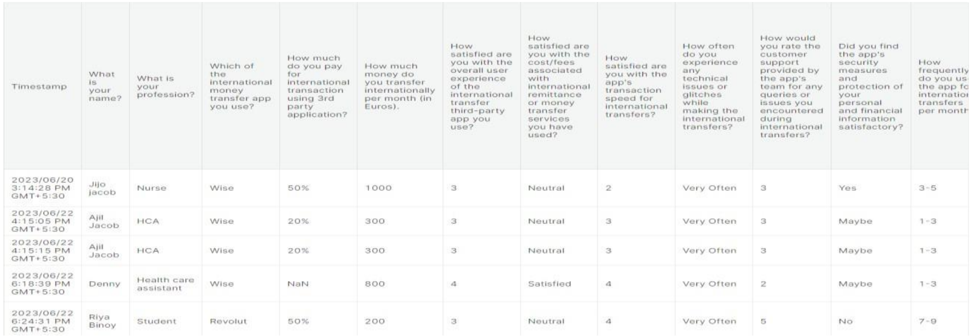
Researchers can increase recipients' overall satisfaction with remittances by understanding the effects of various variables on remittance satisfaction through the analysis of the logistic regression model's coefficients [29].

B. **K Nearest Neighbour (KNN)**: K Nearest Neighbour is neighbourhood based classification or cemeteries-based method. This machine learning is utilised for classification tasks, such as determining how satisfied recipients will be with remittances. In KNN, a class label is given to each instance based on the feature space's K nearest neighbours' dominant class. To get the closest neighbours, the algorithm determines the separation between data points.

C. **Support Vector Machines (SVC)**: Support vector machines create a decision boundary of similarity and ambiguity. Powerful machine learning algorithms like Support Vector Machine (SVM) are frequently employed for categorization tasks like remittance satisfaction prediction. The goal of SVM is to identify the best hyperplane for classifying the data into happy and unsatisfied remittance recipients. The programme finds the hyperplane with the largest margin between the two classes by projecting the input data into a higher-dimensional space.

4. RESULT AND DISCUSSION

Software used for third-party transmissions is essential for enabling cross-border payments between individuals and companies. These kinds of systems have grown in popularity which brings the efficiency, quickness, and affordability. Here it cover four important facets of third-party repatriation technology in this thorough analysis: A) Commission fees, B) safety, C) technological errors and D) feedback from customers.



Timestamp	What is your name?	What is your profession?	Which of the international money transfer app you use?	How much do you pay for international transaction using 3rd party application?	How much money do you transfer internationally per month (in Euros).	How satisfied are you with the overall user experience of the international transfer third-party app you use?	How satisfied are you with the cost/fees associated with international remittance or money transfer services you have used?	How satisfied are you with the app's transaction speed for international transfers?	How often do you experience any technical issues or glitches while making the international transfers?	How would you rate the customer support provided by the app's team for any queries or issues you encountered during international transfers?	Did you find the app's security measures and protection of your personal and financial information satisfactory?	How frequently do you us the app fo internatio transfers per mont
2023/06/20 3:14:28 PM GMT+5:30	Jijo jacob	Nurse	Wise	50%	1000	3	Neutral	2	Very Often	3	Yes	3-5
2023/06/22 4:15:05 PM GMT+5:30	Ajil Jacob	HCA	Wise	20%	300	3	Neutral	3	Very Often	3	Maybe	1-3
2023/06/22 4:15:15 PM GMT+5:30	Ajil Jacob	HCA	Wise	20%	300	3	Neutral	3	Very Often	3	Maybe	1-3
2023/06/22 6:18:39 PM GMT+5:30	Denny	Health care assistant	Wise	NaN	800	4	Satisfied	4	Very Often	2	Maybe	1-3
2023/06/22 6:24:31 PM GMT+5:30	Riya Binoy	Student	Revolut	50%	200	3	Neutral	4	Very Often	5	No	7-9

Figure 1 Data

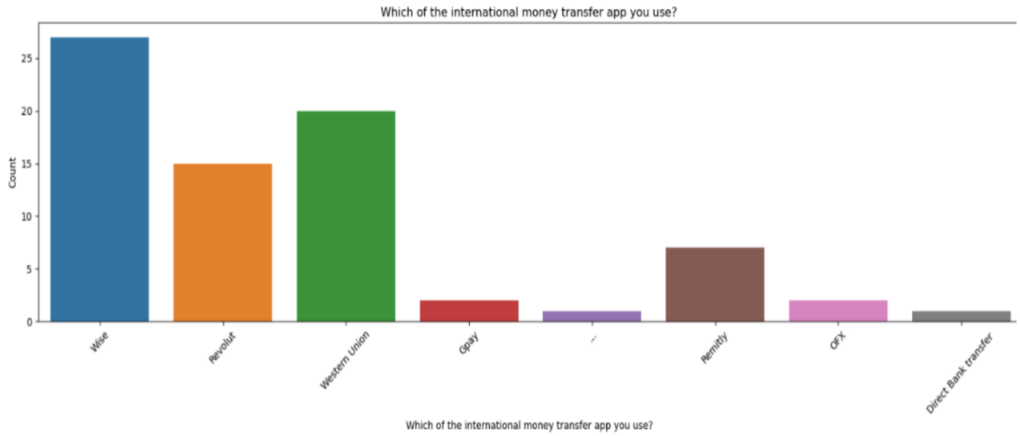


Figure 2 Choice of Application

Figure 3 Commission Charged

Significance of Accurate Pricing: Customers prefer the ability to understand commission costs before selecting a remittance provider. Hidden costs can make consumers unhappy and have an effect on how they feel about the platform as a whole. When compared to conventional financial institutions, third-party transfer software frequently offers more affordable fees for commissions [37]. Exchange rates and other costs that may increase the final cost of the transaction must also be taken into account.

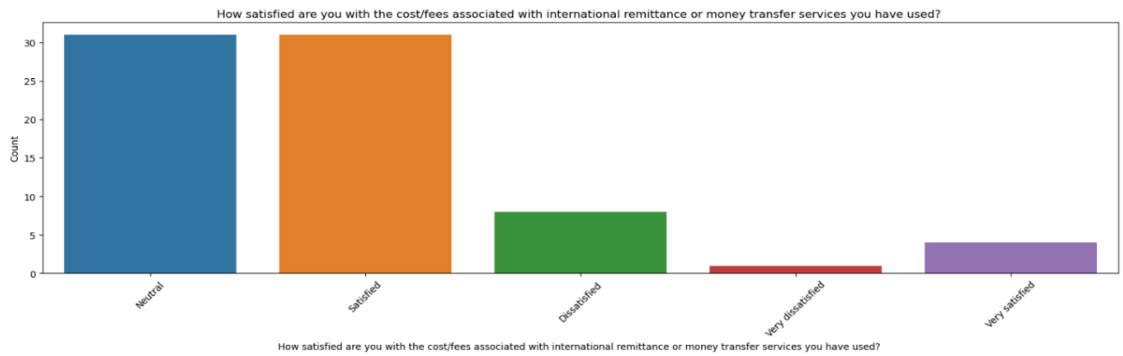


Figure 4 Remittance Software Sentiment

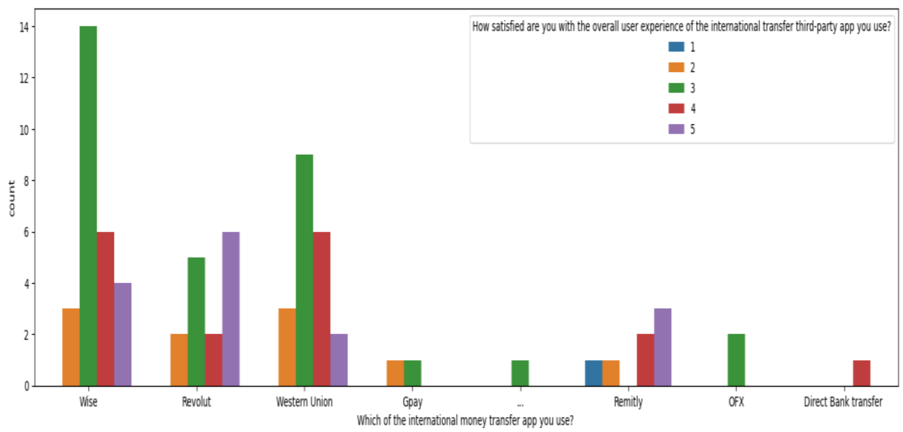


Figure 5 Application based Sentiments.

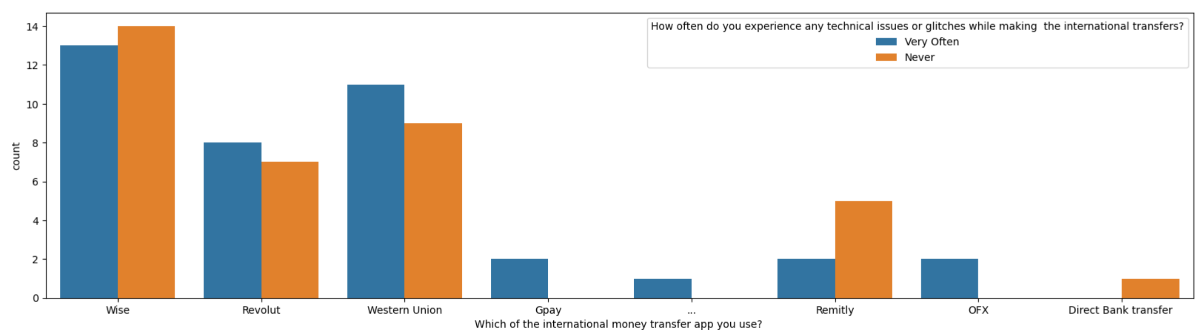


Figure 6 Glitch Comparison

Technological Errors: Technical errors can stall remittances operations and put customers at risk of inconvenience or losses in money.

System Reliability: Independent remittances applications have to have a strong and dependable network that limits outages and technical difficulties in order to preserve client satisfaction.

Customer Support: Quick and effective help for customers is essential for fixing technical difficulties and helping users who are having problems with their payments.

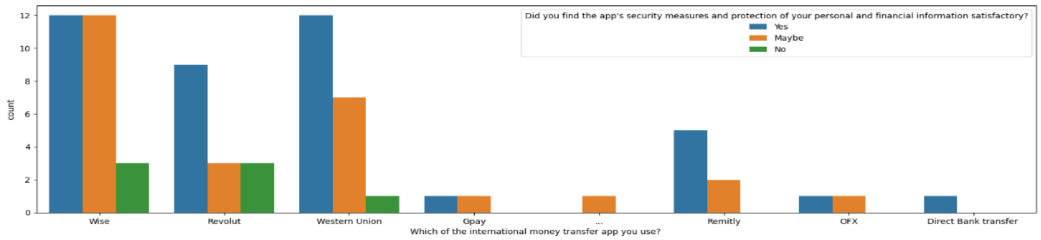


Figure 7 Transfer security Comparison

Security is crucial in the area of remittances because customers anticipate that their personal data and activities will be protected from attacks.

Accountability and Regulation: To maintain the security of operations and safeguard clients from fraudulent activity, reputable third-party remittance providers adhere to pertinent laws and enforcement measures [8].

Technology for third-party transfers has revolutionised international money transfers for individuals and companies. Transmission companies must prioritise open pricing, strict security controls, system dependability, and attentive customer service if they want to stay competitive and earn the confidence of their clients. It is essential to comprehend and handle client sentiments if you want to maintain your position of prominence in this quickly changing sector.

4.1 Machine Learning

i. RandomForest

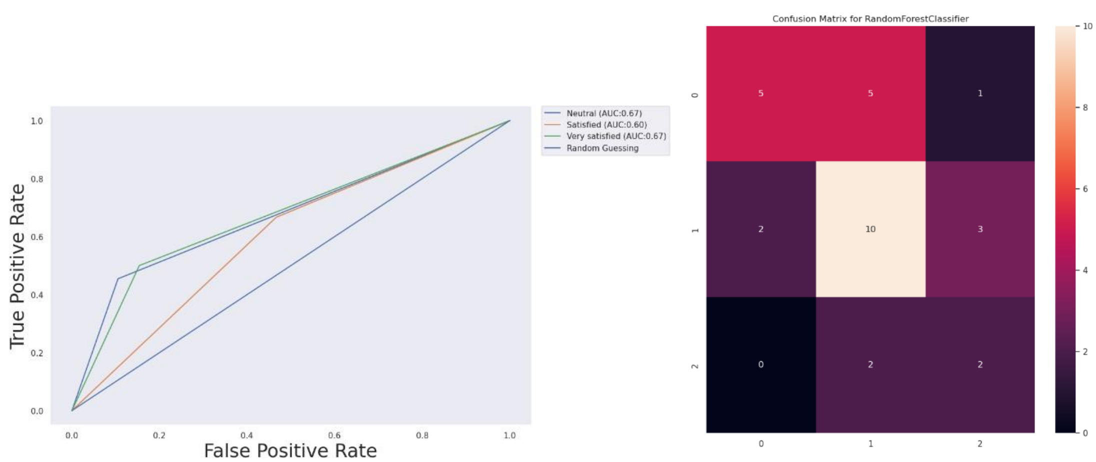


Figure 8 Random Forest Results

The table displays the test data characteristics of performance for three different machine learning models. Gradient boosting classifier, decision tree classifier, and random forest classifier are the models that were tested. True Negatives (TN), False Positives (FP), False Negatives (FN), True Positives (TP), Accuracy, and Specificity are among the measures tracked.

RandomForestClassifier: It produced 4 fake positives and 22 True Negatives in total. Two False

Negatives and two True Positives were accurately detected. This predictive accuracy is determined as the proportion of roughly 0.7111 or 71.11%. The True Negative Rate is a metric for how successfully a model can detect negative events. The calculation is done using the ratio of genuine negatives to the sum of True Negatives and False Positives, resulting about 0.7581 or 75.81%.

ii. Decision Tree

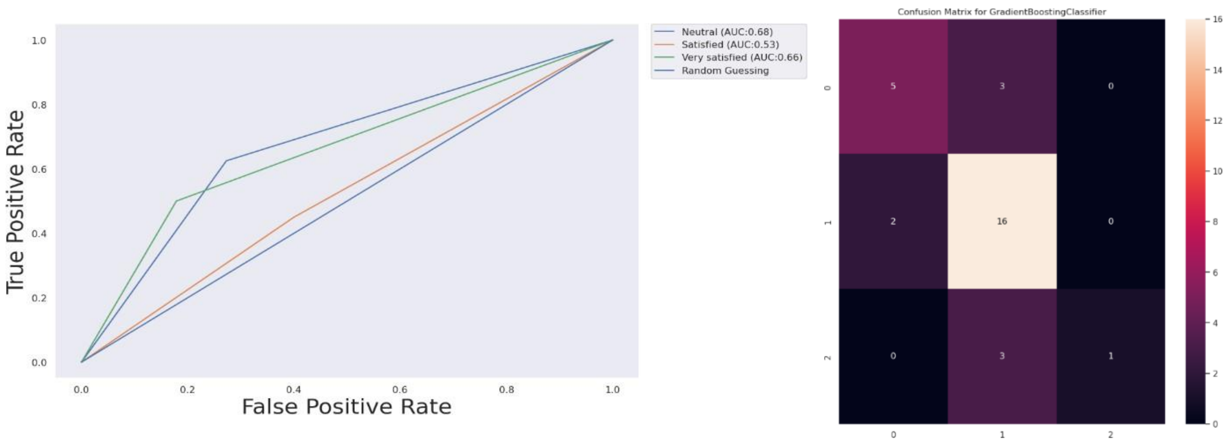


Figure 9 Decision Tree Results

23 true negatives and 5 False Positives were created by the DecisionTreeClassifier. 1 False Negative and 1 True Positive were correctly detected. This estimation's precision is roughly 0.6667, or 66.67%. The Specificity is around 0.7162, or 71.62%, and is computed as the proportion all real negatives to the total of True The drawback and False Positives.

iii. Gradient Boosting

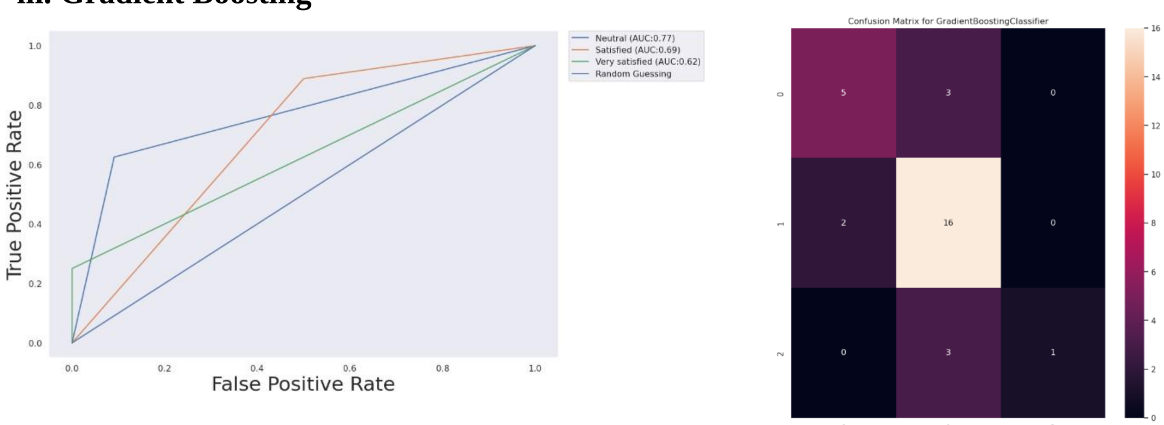


Figure 10 Gradient Boosting Classifier Result

GradientBoostingClassifier: It is the most effective algorithm in terms of accurately recognisingnegative cases, with 26 genuine negatives and 0 False Positives. 3 false negatives and 1 True Positive were registered, nevertheless. This accuracy of the model is roughly 0.8222 or 82.22%. About 0.8030, or 80.30%, is the specificity.

Model	SPlit	TN	FP	FN	TP	Accuracy	Specificity
RandomForestClassifier	Test	22	4	2	2	0.711111	0.758075
DecisionTreeClassifier	Test	23	5	1	1	0.666667	0.716234
GradientBoostingClassifier	Test	26	0	3	1	0.822222	0.803030

Table 2 Comparison Table Machine Learning

The table examines, using a variety of indicators, how three machine learning models performed on an experiment data. The GradientBoostingClassifier performed the best in this evaluation, exhibiting the greatest correctness and specific. The model that's best to use, however, must take into account both the application's distinctive demands and the weight given to certain performance criteria. To choose the right model and optimise it, more investigation and assessment are required.

5. CONCLUSION

Remittances are a substantial source of income for households and neighborhoods in developing nations, and they play a key role in the worldwide economy. For both business organizations and governments to make wise decisions and policies, it is imperative to understand the degree of satisfaction of remittance beneficiaries. For analyzing and forecasting remittance satisfaction, machine learning techniques, particularly algorithms for classification like bagging and boosting, are crucial.

There are various benefits to using ML approaches for remittance satisfaction classification.

The prediction powers of ML models are further enhanced by boosting and bagging approaches. Bagging combines the results of various classifiers to decrease overfitting and boost model robustness. On the other hand, by concentrating on cases that are challenging to categories, boosting iteratively enhances the model's performance. These ensemble techniques provide more precise and trustworthy categorization findings, improving corporate and governmental decision-making.

Measuring remittance satisfaction can help businesses target customers more effectively and provide higher-quality services. The likelihood that satisfied recipients will use remittance services again increases, which boosts customer loyalty and income. Overall, for long-term economic growth and poverty eradication, a thorough understanding of remittances and recipient satisfaction is essential.

Corporate enterprises and governments may harness the power of remittances to bring about positive change and guarantee the welfare of populations around the world by utilizing ML, bagging, and boosting procedures. The remittance sector may promote a relationship that benefits senders, recipients, and the global economy by concentrating on recipient satisfaction.

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