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The Determinant Factors for the Issuance of Central Bank Digital Currency (CBDC) in Malaysia using Machine Learning Framework

Normi Sham Awang Abu Bakar[1,*], Norzariyah Yahya[2], Norbik Bashah Idris[3], Engku Rabiah Adawiah Engku Ali[4], Jasni Mohamad Zain[5], Erni Eliana Khairuddin[6], Ahmad Firdaus Zainal Abidin[7], Sheikh Mohammad Tahsin Murtaj[8], Siti Sarah Maidin[9]

[1,2,3,8]*Department of Computer Science, International Islamic University Malaysia, Gombak, 53100 Kuala Lumpur, Malaysia*

[4]*Institute of Islamic Banking and Finance, International Islamic University Malaysia, Gombak, 53100 Kuala Lumpur, Malaysia*

[5]*Institute for Big Data Analytics and Artificial Intelligence, Universiti Teknologi MARA (UiTM), 40450 Shah Alam, Selangor, Malaysia*

[6]*School of Information Science, Universiti Teknologi MARA (UiTM) 40000 Shah Alam, Selangor, Malaysia*

[7]*Department of Cyber Security, Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA), 26600 Pekan, Pahang, Malaysia*

[9]*Faculty of Data Science and Information Technology, INTI International University Malaysia, Nilai,71800, Malaysia*

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Abstract

In order to identify the factors influencing the establishment of the Central Bank Digital Currency (CBDC) in Malaysia, this study leverages the machine-learning technique to determine the most critical factors leading to CBDC issuance in Malaysia. The overall Central Bank Digital Currency Project Index (CBDCPI) was selected as a target variable, while two machine learning algorithms, Random Forest and XGBoost were utilized to identify the determining variables. These algorithms were chosen for their ability to handle high-dimensional data and provide feature importance scores, which were crucial in identifying the most significant factors. The models were trained and validated using a rigorous cross-validation process to ensure robustness. The accuracy achieved through the Random Forest was 83%, and subsequently, 80% in XGBoost. This study explored a new research frontier by creating two machine-learning models that treated retail and wholesale CBDCPI as target variables. The data used in the process are gathered from various official sources such as the Bank for International Settlements (BIS), the International Monetary Fund (IMF), and the World Bank. The Circulation of Cash, Prevalence of Cryptocurrencies, Effect of CBDC on International Trade, the Search Interest, Financial Development Index, Innovation Value, and Trade Openness are some of the most critical factors determining whether CBDC will be issued in Malaysia. Generally, are identified as important factors determining whether CBDC will be issued in Malaysia. Eventually, the factors identified will be used to develop a framework for the implementation of CBDC in Malaysia.

Keywords: Bank Digital Currency, Machine Learning, Random Forest, XGBoost, Framework

1. Introduction

Fundamentally, a CBDC is a digital banknote. It could be used by individuals to pay businesses or other individuals (a retail CBDC) or it could be used by financial institutions or other wholesale market participants to settle trades in financial markets or other transactions (a wholesale CBDC) [1]. To date, it was reported that, there are 21 countries that have run pilot tests on the usage of CBDC in their economy. One of the biggest implementations of CBDC is in China, which currently reaches 260 million people, is being tested in over 200 scenarios, some of which include public transit, stimulus payments and e-commerce [2]. In relation to that, the motivation behind this study is to investigate the determinant factors on the success of the CBDC implementation in other countries and thus, finding the best application framework of CBDC in Malaysia.

Over time, a variety of innovative payment methods have evolved to meet societal demands. The development of means of payment led to the creation of banknotes, credit cards, cheques, and coins. Later, printed money gave way to digital

*Corresponding author: Normi Sham Awang Abu Bakar (nsham@iium.edu.my)
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currency in the wake of technological progress. Thus, distributed ledger technology (DLT) and other advances in the financial world have enabled the introduction of digital currencies. Moreover, the concern that various cryptocurrencies such as Libra, Ethereum, and Bitcoin could take control of the financial system has prompted the central bank to initiate the issuance of CBDC. In a report published in 2020, Bank Negara Malaysia (BNM) displayed a comparison between digital assets (Cryptocurrency, stablecoins) and CBDC. This report explains that digital assets can be classified as exchange, utility, or security tokens depending on whether they provide rights of ownership, return of a principal sum, or participation in future earnings. The term "Cryptocurrency" is commonly used to refer to these privately issued digital assets.

Cryptocurrencies have proven to be promising in several areas, however, they also have major drawbacks. One of the main disadvantages is the high price fluctuation. In 2023, for instance, Bitcoin's price may fall by 40%, from its current \$17,000 to \$10,000 [1]. Furthermore, cryptocurrencies are prone to slow transaction rates, as Bitcoin can only process 3.3 transactions per second, while conventional systems can process more than 3000 transactions per second. Therefore, stablecoins, a new type of digital currency, were created to counteract the disadvantages and volatility of cryptocurrencies. Some stablecoins have a value tied to tangible assets such as gold, while others have a value tied to national fiat currencies, e.g. US Dollar. It is therefore possible that stablecoins will one day be widely used in retail payment systems. However, stablecoins suffer from several economic risks, including solvency against the currency they are tied to, liquidity of the value, exposed to fraud and illicit activities [2].

Another type of digital currency is CBDC which is issued and governed by a nation’s central bank. Unlike cryptocurrencies like Bitcoin (BTC) or Ether (ETH), which are decentralized and operate on public blockchains, CBDCs are centralized and typically operate on a permissioned blockchain, meaning access is controlled by the governing authority (i.e., the central bank) [3]. The primary purpose of CBDCs is to digitalize the fiat currency of a particular nation, enabling seamless and direct transactions between the central bank and the citizens without the need for intermediaries. CBDCs transfer value directly from one entity to another without traditional banking delays or fees. By design, CBDCs aim to integrate the advantages of digital assets while being backed by the trust and authority of a nation’s central bank.

To combat the privately issued digital currencies and their impact on Malaysia's economy, the Central Bank of Malaysia (Bank Negara Malaysia) has embarked on the research and development of a cross-border wholesale CBDC to be held in September 2021. The first phase of BNM’s CBDC project initiatives include facilitating international transactions between financial institutions and creating a shared platform for cross-border settlements. The initiative is Project Dunbar, which leverages the benefits of multiple CBDCs (mCBDC) on DLT platforms in collaboration with BIS Innovation Hub, Reserve Bank of Australia, Bank Negara Malaysia, Monetary Authority of Singapore, and South African Reserve Bank. In addition, the implementation of domestic wholesale CBDCs and retail CBDCs is planned in the last two phases of the proof-of-concept roadmap [4]. Project Dunbar aims to explore the potential benefits and opportunities of a multi-CBDC platform, understand the critical obstacles and challenges to implementing such a platform, develop design approaches to address them, and prove the viability of the concept through the building and testing of technical prototypes. A common platform for international settlements using CBDCs could bring about significant improvements to cross-border payments, much like how national payments systems have made domestic payments seamless, instant and low cost in many countries. At the same time, this new type of arrangement also brings new challenges. This project is a significant progress for BNM from the point of view of the CBDC adoption plan for Malaysia.

CBDC is typically issued in response to local circumstances due to its strong potential as a beneficial instrument in accomplishing policy priorities. According to BNM, the circulation of cash, the prevalence of the use of cryptocurrencies, and the effect of CBDC on international trade are some of the most critical factors that will determine whether CBDC will be issued in Malaysia. In this study, Machine Learning (ML) is used to create a robust framework that determines the most critical factors that lead to CBDC issuance in Malaysia. The data used in the process are obtained from various official sources such as the BIS, IMF, and World Bank. The problem is treated as a classification problem with the total, retail, and wholesale index of the CBDC project as the target variables. Therefore, the random forest classifier and the XGBoost classifier are used to build three machine-learning models and extract the key features that lead a country to accelerate the issuance of CBDCs.

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1.1. Review Of Previous Works

The following section discusses related work on CBDC, focusing on CBDC implementation and the advantages and disadvantages of CBDC.

1.1.1. Definition of CBDC

CBDC is often defined as digital legal tender which the definition was proposed by the IMF [2]. According to Brookings International, a CBDC is a digital version of a fiat currency issued by the central bank [3]. While European Central Bank defines CBDC as an electronically administered currency issued by a central bank and usable by the general public [4]. Another definition provided by the Bank for International Settlements stated that CBDC is electronic money issued by the central bank, which would be available to the public at retail. At the same time, wholesale CBDCs could be a fresh mechanism for bank settlement [5].

CBDC is a new type of central bank electronic liability that can be used as a means of payment and store of value while retaining most of the desirable properties of M0 and M1, the method of measuring the money supply. Based in the findings of Lee et.al [6], CBDC is intended to serve as a medium of exchange, store of value, unit of account, and standard for deferred payments. In addition, CBDC has two components: the business structure and the ledger structure [6]. CBDC ledgers are token-based or account-based. An account-based system seems to be most suitable when access and identity verification are prioritized in wholesale CBDC (interbank payments). A user must have their identity as an account holder confirmed by a third party and have sufficient funds to make a payment. With token-based CBDC, on the other hand, customers can prove their identity by signing a transaction with the private key of a token. Some token-based infrastructures also offer account-based and multi-factor authentication.

However, in this research, the expanding CBDC-related literature has narrowed into two key concerns:

1) Whether CBDCs are preferable as a replacement for physical currency and the method by which central banks should generate digital currency for retail use [7], [8].
2) How to deal with the potential liabilities, and volatility CBDCs may pose to the financial and monetary systems [9], [10].

The analysis by Kochergin & Dostov [11] demonstrates that distinct strategies for adopting CBDCs demand distinctive actions from central banks. To ignite people's interest in CBDC, the monetary authorities should take action by lowering interest rates and raising deposit rates. The study also shows that the CBDC's implications on the financial and banking system depend on the degree of convergence between the two systems. Changes in the circulation of money are inevitable with the widespread adoption of CBDC in the retail sector, as digital currency gradually replaces traditional means of payment. For this reason, the central bank will set a fair interest rate and deposit rate, and the quantity of newly created currency will eventually decrease. As a result, commercial banks will face more competition if the deposit rate at central banks is high.

In addition, wholesale CBDC will impact the real-time gross system as it will be replaced by cross-border CBDC. International trade will be processed through it. In addition, the wholesale CBDC can provide continuous support to the general public, reduce the number of intermediaries in trade, and upgrade the existing system to support a unified set of payment standards. However, for countries with weak financial systems, the introduction could be too expensive [11].

In peer-to-peer lending (a type of financial technology that bypasses banks and lets individuals lend or borrow money from one another), big data and ML are used in highly complex ways to assess customer data [12]. Based on detailed credit transaction data from a different Chinese fintech industry frontrunner, Gambacorta et al. [13] found that ML algorithms, unlike traditional models, provide more accurate estimates of the default risk of borrowers, especially when a negative supply shock leads to a decrease in production and an increase in prices.

Similarly, Kiff et. al. assert that, the demand for CBDC in specific regions or industries can be predicted using ML algorithms based on classification tasks [2]. The data collected in the detailed analysis would lead to a better understanding of CBDC and could help forecast and develop macroeconomic incentives. For example, central banks might utilize the information gathered to finance management and deposits or calculate the natural money supply using ML or other sophisticated quantitative models.

1.1.2. CBDC Strengths and Weaknesses

According to Andolfatto [14], CBDC can reduce the demand for paper notes as the issuance of paper notes encourages more people to keep their money in banks, forcing banks to lower deposit rates. Moreover, it was also speculated that CBDC's fiscal policy would lead to market instability. However, [15] proposed that CBDC would improve market stability by increasing central bank deposits via pass-through funding.

In addition, central banks are very concerned about the prospect of people favouring CBDC accounts over commercial bank accounts and the impact on the financial system in general. Raskin and Yermack [16] explored that a digital currency issued by state-owned banks would discourage people from keeping deposits in commercial banks and that people would gravitate towards central banks. Therefore, to maintain a balance, commercial banks and financial service providers must be responsible for issuing wallets and managing apps, while central banks are responsible for issuing the value of CBDC and authenticating it [17]. According to Fernández-Villaverde [18], central banks would act as a middleman between commercial banks and financial service providers for account-based CBDCs. This would allow the public to hold an account directly with the state bank. Overall, CBDC proponents argue that CBDC will make banking and transaction processes more secure and efficient [19].

From the case studies in other countries, the gap in the CBDC implementation in Malaysia is the investigation on the factors that influence the issuance of the digital currency. The significance of the research is the identification of the important factors for CBDC implementation using ML techniques. The main objective of this research is to identify and design the infrastructure or model that could support the CBDC issuance by the central bank in Malaysia.

2. Method

From the objective of this research, it is necessary to collect the data that have effects on CBDC. Therefore, this can be boiled down to identifying the most significant influencing factors impacting a country's technological faculties and good governance and utilizing retail or wholesale CBDC project index score as the target variable. To this end, we use ML methods to predict the CBDCPI and data mining, the most crucial factors for our model construction. The overall methodology of this research is given in figure 1.

2.1. Data Description

The first step is to collect the right data to be used in this research. Gathering appropriate domain datasets is the starting point for each ML-based research. The data for this research datasets are taken from the World Bank, the IMF, and a BIS working paper. Then all the datasets are merged into one by using Python libraries. The dataset being used spans from 1990 to 2021 and includes more than 190 separate nationalities and territories with 24 different variables. Matsui and Perez [20] mentioned that the dataset can be categorized according to the characteristics of the dataset such as the availability of Internet infrastructure, the rate of economic growth and financial integration, the nature of institutions, the culture of invention, demographics, and the frequency of international trade. China’s central bank first initiated CBDC development in 2014, and Sweden’s central bank began researching the establishment of digital currency in 2017 [21]. Therefore, we have only covered the average of each feature from 2015 to 2021, although the dataset used in this research has data ranging from 1990 to 2023.

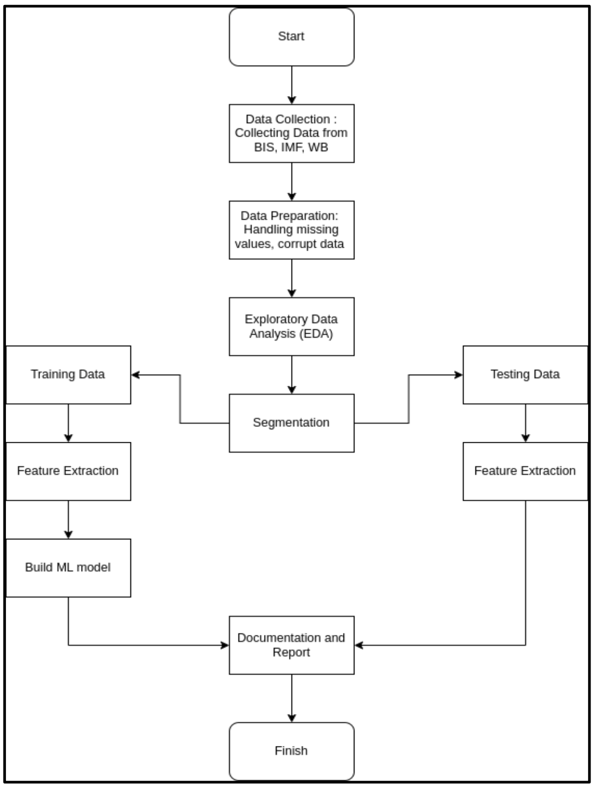

Figure 1. Research methodology

2.2. Data Preparation

Data preparation or cleaning is an important step in ML research. However, it takes a lot of time and is the most tedious component of data science, as insufficient or low-quality data can compromise the veracity of findings or lead to false conclusions. Careful data preparation minimized the possibility of errors and deficiencies and prepared the data for testing and implementing ML models. In the data cleaning process, there are some variables with missing values is identified for an example “Innovation_Score” and “Account_Ownership”, which have more than 40 missing values. To handle the missing values, a Linear Regression model was employed. Initially, the dataset was pruned to exclude irrelevant columns. Columns with missing values were isolated for further processing. Rows with a specific number of missing values were removed to reduce their impact on the dataset.

The Linear Regression model was then trained on this cleaned dataset, excluding the columns with missing values. This model was chosen due to its ability to handle numerical data and its effectiveness in predicting missing values based on the relationships between variables. The missing values in the isolated columns were then predicted using this trained model. The advantage of this approach is that it considers the correlation between these columns and other features in the dataset, providing a more accurate prediction for the missing values.

2.3. Exploratory Data Analysis

Visualization techniques were employed to comprehend better the interrelationships between the data's attributes and spot patterns. Furthermore, Exploratory Data Analysis (EDA) paints a picture of the dataset as a whole, examines it prior to any hypotheses being made, identify outliers or unusual occurrences, and unearth intriguing correlations among features. EDA significantly enhances an analyst's fundamental comprehension of several factors. **Error! Reference source not found.** shows the relationship between two variables using the Pearson correlation coefficient [22], this quantifies how closely two variables are related linearly. It’s worth is between -1 and 1, depending on the following criteria:

1) A correlation of -1 implies a negative linear relationship when comparing two variables
2) No linear relationship exists between two variables if the value is 0
3) A correlation coefficient of 1 shows a strong positive linear relationship between two variables

For a given pair of variables, the strength of their association is indicated by how far their correlation coefficient deviates from zero. In figure 2, the correlation between "Government Effectiveness" and "Innovation_Score" is 0.90, which means there's a substantial positive correlation between both variables. It indicates that if a country's government can deliver high-quality public services and sound policies consistently, its citizens will be more inclined to be creative and entrepreneurial.

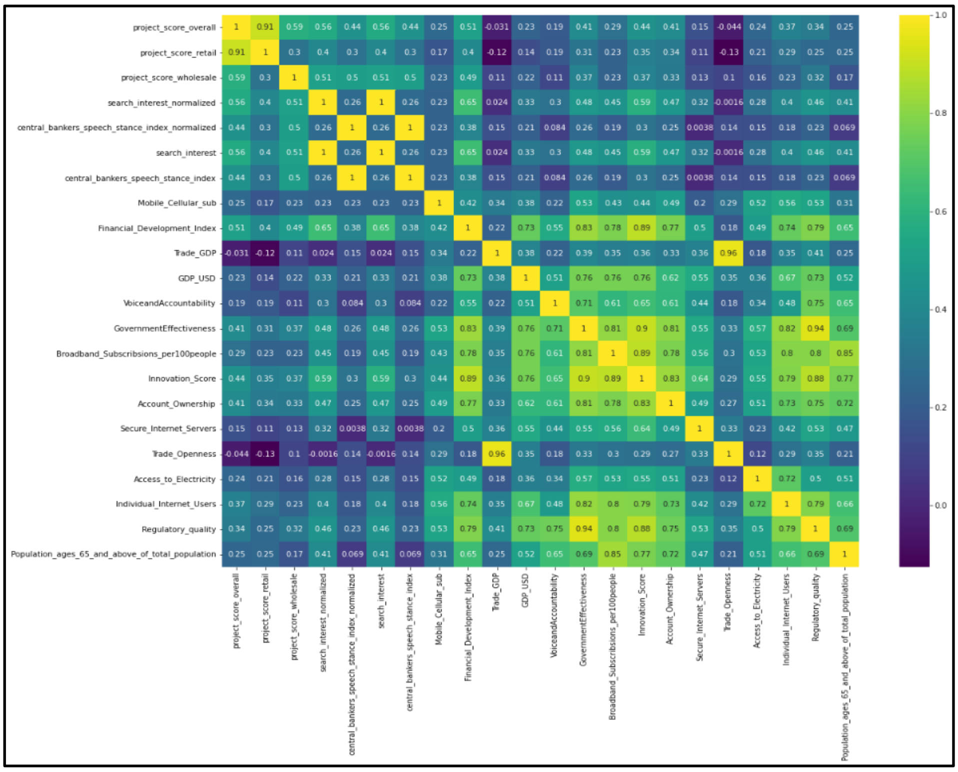

Figure 2. Correlation Matrix of the dataset

Moreover, figure 3 shows that countries with higher CBDCPI tend to have high Government Effectiveness and Innovation scores, which supports the strong correlation between those two variables as illustrated in figure 2. Figure 4 shows that more economically advanced regions having CBDCPI 2 and 1 have an immense need for creative methods of wholesale settlement. It supports the strong positive correlation between Financial_Development_Index and Innovation_Score in figure 2 which is 0.89.

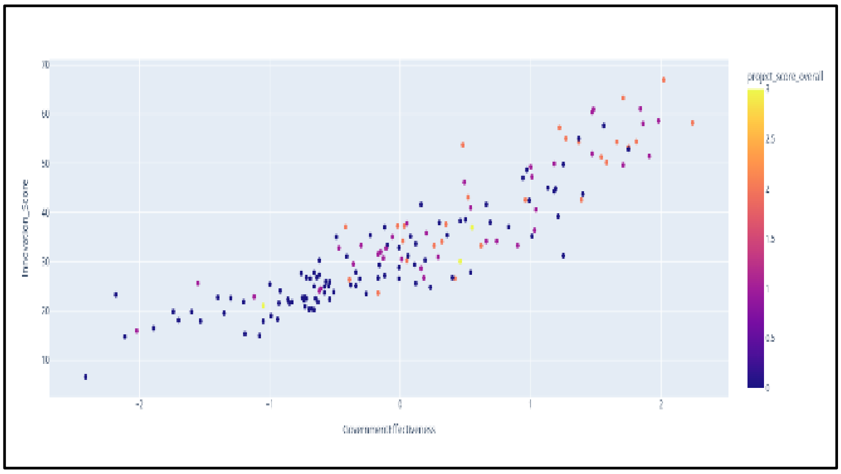

Figure 3. Impact of Government Effectiveness on Innovation_Score for the Overall CBDCPI

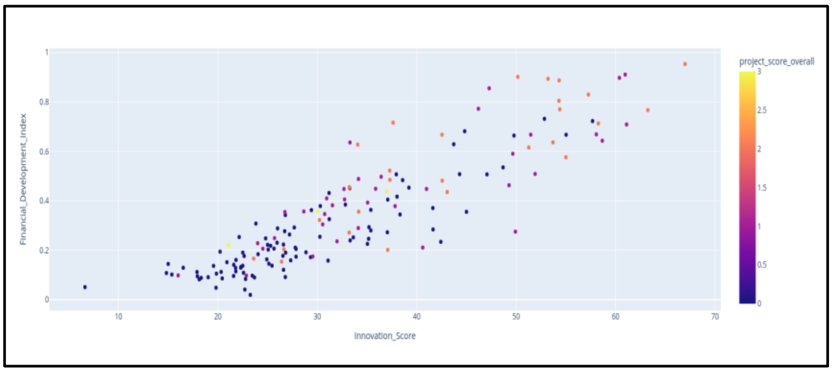

Figure 4. Impact of Financial_Development_Index and Innovation_Score on the Overall CBDCPI

Figure 5 presents a scatter plot, elucidating a robust positive correlation between Government Effectiveness and Regulatory Quality. This visual representation substantiates the correlation coefficient of 0.94, as previously quantified in figure 2. This indicates that effective governments are likely to have high-quality regulations. These regulations, in turn, foster a conducive environment for economic development and societal well-being. Consistent delivery of high-quality public services and sound policies by a country's government can lead to a robust regulatory framework, promoting private sector development and overall economic stability.

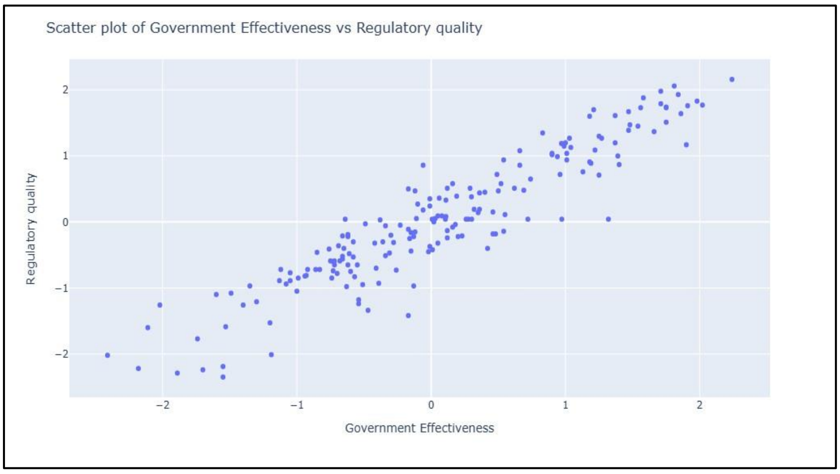

Figure 5. Scatter Plot of Government Effectiveness vs Regulatory Quality

Figure 6 presents a scatterplot matrix encompassing selected variables, namely 'Government Effectiveness', 'Financial Development Index', 'Individual Internet Users', and 'Project Score Overall' (also referred to as CBDPI). This matrix offers a comprehensive visual exploration of the pairwise relationships and respective distributions of these variables.

The matrix distinctly manifests robust positive correlations between 'Government Effectiveness' and 'Financial Development Index', as well as 'Individual Internet Users' and 'Financial Development Index'. These correlations imply that the effectiveness of governance and the level of financial development are pivotal determinants influencing both internet usage among individuals and the overall project score (CBDPI). This analysis underscores the integral role of effective governance and robust financial systems in fostering digital inclusivity and driving project success, as measured by the CBDPI.

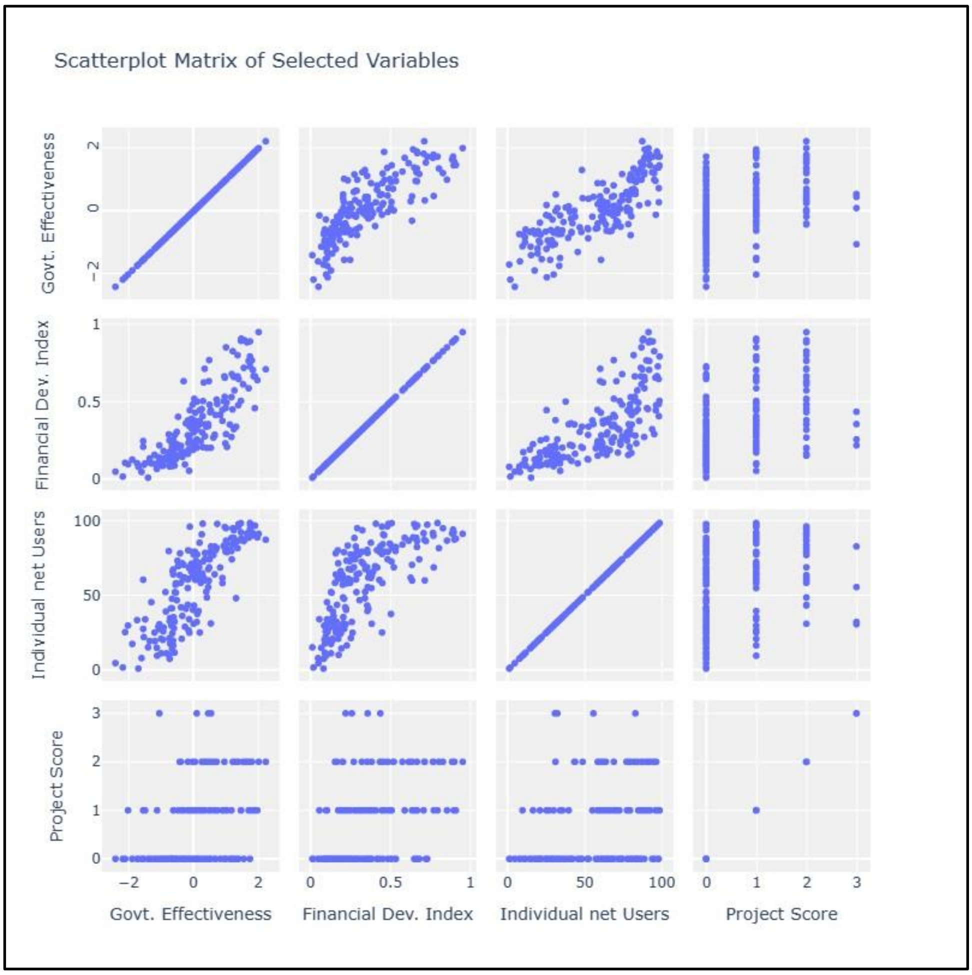

Figure 6. Scatterplot Matrix of Government Effectiveness, Financial Development Index, Individual Internet Users, and Project Score Overall.

2.4. Feature Selection

Feature selection is an essential stage in model building that enhances the performance and interpretability of ML models by choosing the most relevant characteristics from the dataset. This subsection provides a detailed explanation of the feature selection process used in our research.

2.4.1. Initial Feature Pool

The original feature pool included all variables from the combined dataset sourced from the World Bank, the IMF, and a BIS working paper. The variables encompassed a broad array of socio-economic, technological, and governance indices from 1990 to 2023.

2.4.2. Feature Filtering

To ensure that only relevant features were included in the analysis, several filtering techniques were employed. These techniques included:

Correlation Analysis: Features exhibiting high correlations with the target variable, CBDCPI, were given preference. This was done to ensure that only features strongly associated with the target variable were retained.

Domain Expertise: Input from domain experts was leveraged to identify features that were theoretically and empirically linked to a country's technological capabilities and governance quality. Features deemed irrelevant or redundant were eliminated from further consideration.

2.4.3. Feature Importance Techniques

Tree-based feature importance technique was employed to rank the remaining features based on their relevance to predicting the CBDCPI.

Tree-based Methods: Ensemble tree-based algorithms such as Random Forest and Gradient Boosting were utilized to evaluate the importance of each feature in predicting the target variable. Features with higher feature importance scores were prioritized for inclusion in the final model.

2.5. Model Validation

In the development of the ML model, a robust validation process was employed to ensure its reliability and accuracy. We utilized a k-fold cross-validation technique, specifically a 5-fold validation, to assess the model's performance. This method involves dividing the dataset into five subsets, training the model on four subsets and validating on the remaining one in each iteration. The process was repeated five times, and the average performance metrics were computed. The application of k-fold cross-validation enhances the model's robustness by providing a more comprehensive evaluation across different subsets of the data, minimizing the risk of overfitting.

Additionally, we employed Stratified K-Fold Cross-Validation for further model robustness assessment. The outcomes showed a mean accuracy of 0.710 with a standard deviation of 0.041, signifying consistent performance across diverse data subsets.

3. Results and Discussion

Matsui and Perez reported that, there are two sub-indices within the data set presented in: the retail CBDCPI and the wholesale CBDCPI [20]. The wholesale CBDCPI is intended for financial institutions that hold reserve deposits at a central bank. The retail CBDCPI, on the other hand, is designed to replace cash and is intended for the general public and retailers. The maximum of these two sub-indices is the total CBDC project index of a country. For example, if the retail CBDC project index of a country is 1 and the wholesale CBDC project index is 2, then the total CBDC project index of that country is 2.

3.1. Prediction Model

Since the index values of the CBDC project are categorical, a random forest classification model was constructed for its prediction [20]. To construct the model, first, data were on 162 countries using the methods described in Section 3.1. Then the variables are narrowed down the available variables to 24. The original set of 24 variables was narrowed down to 17, after which dependent and independent variables were defined. Then, a training set were created and a test set with these variables. With random state = 42 the method would then perform random sampling with a probability of 42. All other settings were left at their default values [23]. Algorithmically, bootstrap sampling would partition the data and create new variables for each tree. To reach a conclusion, the algorithm would go through a process of training and validating all relevant variables.

The output would be the conclusion reached by majority voting as trees generate conclusions [24]. In addition, another model was trained using the XGBoost classifier with all parameters preset. After both models were trained on the training set and the predictions were performed on the test set, the accuracy values were determined using the actual and predicted values. The accuracy of the two models is shown in table 1. It shows that the accuracy of the random forest classifier in the test group is 83%. It is higher than the accuracy determined in [20], which is 77% and 68% for the test set of aggregated data.

Table 1. Accuracy score of the classifiers taking Overall CBDCPI as the target variable.

Classifier	Train	Test
Random Forest	1.0	0.83
XGBoost	1.0	0.80

The 10 key characteristics identified by Random Forest to better understand the aspects of a country that motivate a country to develop CBDC are shown in figure 7. Search interest proved to be the most important feature of the random forest model, followed by the financial development index and mobile phone connectivity.

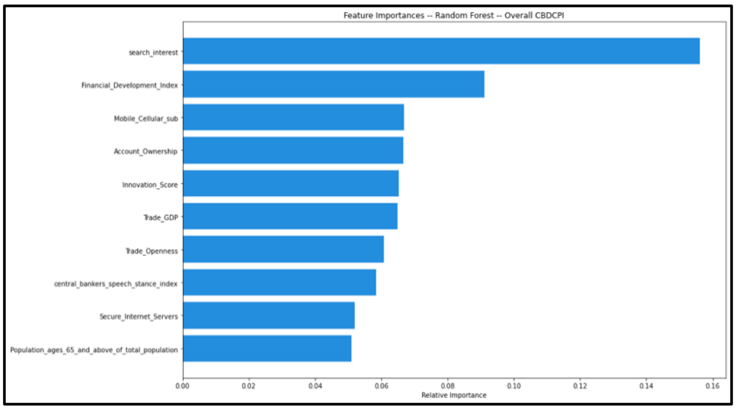

Figure 7. Top 10 features of overall CBDCPI using Random Forest

When using the XGBoost classifier model, the top 10 features found are displayed in figure 8. In this model, search interest was also the most important factor, followed by the central bank language index and the degree of openness of markets to foreign trade or trade openness.

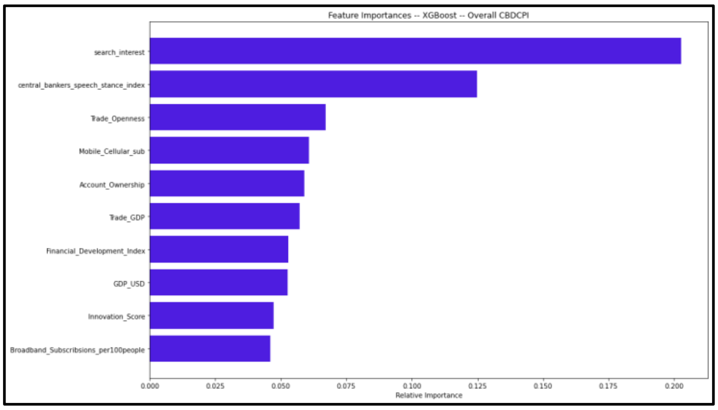

Figure 8. Top 10 features of overall CBDCPI using XGBoost.

3.2. Retail CBDC Project Index

In order to predict the CBDC project index for the retail sector of a country, two models were implemented using the CBDC project index for the retail sector as the target variable, in contrast to the model implementation described in Section 3.1. Thus, two additional models where the CBDC retail project index is the target variable instead of focusing only on the total CBDC project index of a country were developed. The wholesale CBDC project index was also used in Section 3.3 to train two additional machine-learning models. In light of this, a new boundary was set for the research. The results of the accuracy of random forest and XGBoost are presented in table 2, with the retail CBDC project index serving as the dependent variable. While the testing set only comprises two data points, the training set for each model contains eight different data points. The random state has been changed to 42, and all other parameters have been left at the default values.

Table 2. Accuracy score of the classifiers taking Retail CBDCPI as the target variable

Classifier	Train	Test
Random Forest	1.0	0.85
XGBoost	1.0	0.82

The top 10 features determined by random forest that motivate to work towards retail CBDC are displayed in figure 9. Search interest ranked first, followed by the financial development index and trade openness.

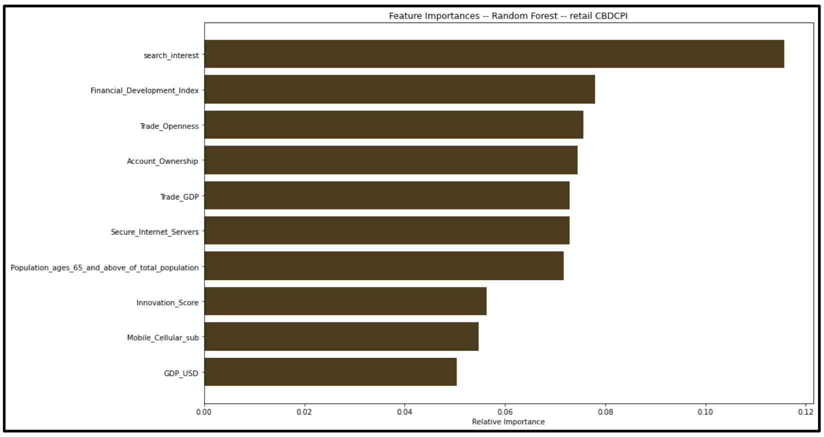

Figure 9. Top 10 features of retail CBDCPI using Random Forest.

3.3. Wholesale CBDC Project Index

Two more models have been deployed, with the wholesale CBDC project index as the dependent variable, as mentioned in Section 3.2. Table 3 displays the model accuracy, which is the best of any model used in Section 3.1.

Table 1. Accuracy score of the classifiers taking Wholesale CBDCPI as the target variable

Classifier	Train	Test
Random Forest	1.0	0.91
XGBoost	1.0	0.94

Key features are identified using the random forest and XGBoost classifier models to identify likely drivers for wholesale CBDC implementation, as the models built with the wholesale CBDC project index provide higher accuracy. The top 10 characteristics identified by Random Forest are shown in figure 10, where Search interest ranks first, followed by the financial development index and innovation value.

This result is in line with the results of Allen et. al. [12], where they investigated a number of features that influence the CBDC adoption in China. They found that Search interest, financial development index and innovation value are among the top 5 features that influence CBDC adoption in China.

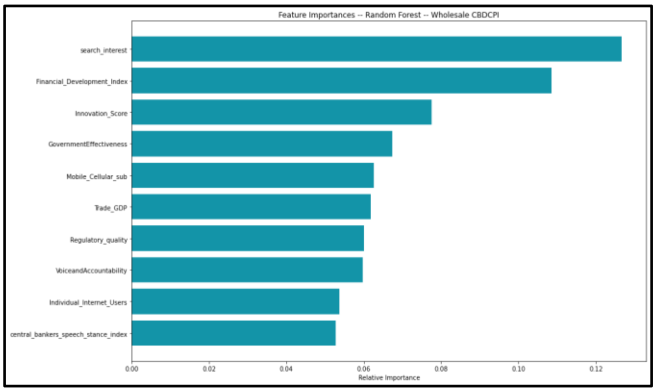

Figure 10. Top 10 features of Wholesale CBDCPI using Random Forest.

The 10 most important features of the XGBoost classifier are shown in figure 11. Search interest is also the most important feature in this model, followed by the innovation score and the index of central bank speech.

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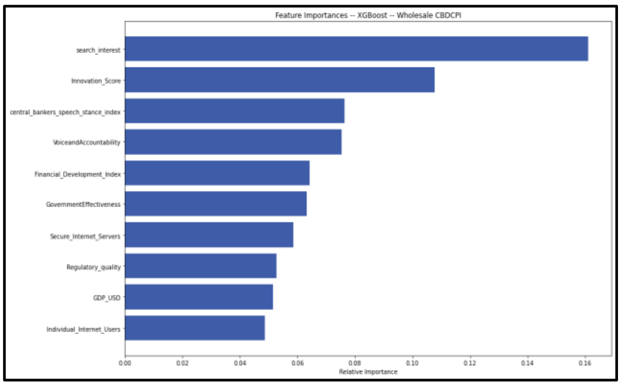

Figure 11. Top 10 features of Wholesale CBDCPI using XGBoost

4. Conclusion

The BNM is continuously conducting research that will lead to the issuance of CBDC in Malaysia. This is despite the fact that Malaysia has no plans to do so in the near future. In this study, ML techniques were utilised to extract the key factors that will initiate CBDC in Malaysia. In all the models created in the above section, search interest was found to be the most important factor, followed by financial development index, innovation value, and trade openness. The list of the factors is represented in figure 12. Search interest indicates public interest in a digital currency, mostly a currency backed by government agencies and central banks adopting CBDC [5]. Similarly, and in the interest of the public, BNM is focusing its efforts on the study and development of CBDC, which would play an essential role in the country's payment infrastructure and place Malaysia in a position of financial stability.

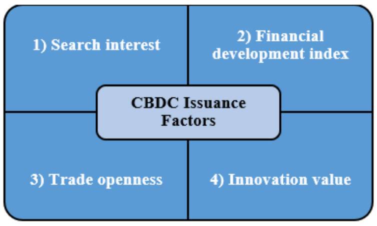

Figure 12. Factors for CBDC issuance in Malaysia

4.1. Limitations and Future Work

Apart from the factor that led to the issuance of CBDCs in Malaysia, the exploratory analyses outlined in Section 2.3 also revealed that citizens are more likely to be innovative and enterprising when it comes to CBDCs if their government can consistently provide high-quality public services and sound policies. Additionally, countries with higher CBDCPIs typically have higher scores for innovation and government effectiveness that led to the CBDC issuance.

Besides the factors being investigated, there are other possible factors that could be considered in this study, such as: internet infrastructure, economic growth rate, and demographics. However, due to the difficulties to get the data, the factors were not considered in this phase. For future work, the factors may be considered for analysis and included in the framework development, once the data are available.

4.2. Suggestions for CBDC Implementation

Based on the results obtained from the study, a few suggestions are provided to provide insights to the policy makers in Malaysia:

1) A CBDC offers a wide range of innovative opportunities. Some come from the unprecedented transparency that a CBDC would provide regulators, such as the capacity to obtain a comprehensive yet detailed picture of global spending in an economy. In order to create highly targeted monetary interventions in a national economy, these opportunities would also include new monetary policy levers, such as the ability of central banks to impose

negative nominal interest rates, create currency with time limits, or impose other spending requirements (such as required spending on durable goods).

2) The results show that Government Effectiveness influence the Innovation scores of CBDC adoption in the related countries. The policymakers should focus on improving the effectiveness in the governing policy of CBDC and also the monitoring of the policy implementation.
3) Effective governments are likely to have high-quality regulations. These regulations, in turn, foster a conducive environment for economic development and societal well-being. Consistent delivery of high-quality public services and sound policies by a country's government can lead to a robust regulatory framework, promoting private sector development and overall economic stability.

5. Declarations

5.1. Author Contributions

Conceptualization: N.S.A.A.B., N.Y., N.B.I., E.R.A.E.A., J.M.Z., E.E.K., A.F.Z.A., S.M.T.M., and S.S.M.; Methodology: N.Y.; Software: N.S.A.A.B.; Validation: N.S.A.A.B., N.Y., N.B.I., E.R.A.E.A., J.M.Z., E.E.K., A.F.Z.A., S.M.T.M., and S.S.M.; Formal Analysis: N.S.A.A.B., N.Y., N.B.I., S.M.T.M.; Investigation: N.S.A.A.B.; Resources: N.Y.; Data Curation: N.Y.; Writing Original Draft Preparation: N.S.A.A.B. and N.Y.; Writing Review and Editing: N.Y. and N.S.A.A.B.; Visualization: N.S.A.A.B.; All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

5.3. Funding

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5.4. Institutional Review Board Statement

Not applicable.

5.5. Informed Consent Statement

Not applicable.

5.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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