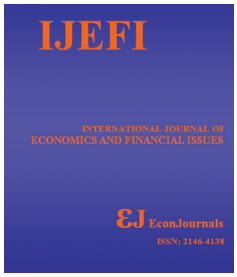

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Does Financial Inclusion and Digitalization Reduce Corruption? Cross-Country Evidence and Sectoral Insights

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ABSTRACT

This study investigates the impact of key economic and financial variables on the Corruption Perception Index (CPI) across countries. The objective is to identify the most significant predictors of perceived corruption. The analysis employs a variety of quantitative methods, including Linear Regression, Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Attention-RNN, and Random Forest models. The results demonstrate that GDP per capita is the most influential factor in explaining variations in corruption perceptions. Among financial sector indicators, variables reflecting active banking operations (such as outstanding loans and deposits) showed stronger predictive power than digitalization metrics (e.g., number of bank branches and ATMs). This suggests that the intensity of financial activity plays a more critical role than the mere availability of banking infrastructure. The study concludes that fostering economic growth and stimulating active engagement with the formal financial system are effective strategies for reducing corruption perceptions. Policy recommendations include addressing unemployment and promoting the formalization of remittance flows.

Keywords: Financial Inclusion, Digitalization, Corruption, Economic Growth
JEL Classifications: C58, G21, G18, O4

1. INTRODUCTION

Digitalization, financial inclusion, and corruption are interconnected issues that exert significant impacts on the economy. Digitization serves as an effective tool in combating corruption and enhancing equitable access to financial services. However, its efficacy depends on several factors, including the efficiency of policy implementation and the effectiveness of governmental performance (Hasan and Lu, 2023; Yamen et al., 2023).

Digitalization has profoundly impacted the global landscape, creating new opportunities and complex challenges across various domains, particularly in governance and economic growth. With the increasing adoption of digital technologies, especially artificial intelligence, in the financial sector, there arises an urgent need to address the ethical dimensions associated with these technologies, ensuring their deployment in a manner that is fair, transparent, and accountable. Awareness is growing regarding the importance of strategically integrating digital technologies as a pivotal tool for promoting equitable access to essential services, enhancing efficiency, and increasing transparency. This perspective is grounded in the fundamental hypothesis that digitalization can serve as an effective instrument in combating corruption on a global scale and fostering financial inclusion, particularly in regions where these challenges hinder the achievement of sustainable development (Hundal, 2024) (Kussainov et al., 2023). Furthermore, enhancing information management and developing analytical skills are fundamental factors in preventing and detecting financial irregularities (Duoqi, 2011).

Digitalization constitutes an effective mechanism for combating corruption, as it enables a diverse array of methods to mitigate

corruption within the financial sector by providing innovative solutions to chronic issues related to transparency and accountability (Shen et al., 2025; Stepanov and Basangov, 2023). The increased transparency of financial transactions and expenditure processes reduces opportunities for clandestine practices and misappropriation of funds. Moreover, modern technologies, such as blockchain, possess significant potential to transform the methods of storing and securing financial records. This technology contributes to enhancing the reliability of financial institutions by establishing a distributed and immutable ledger, thereby making data manipulation and fraudulent activities more difficult (Maliarchuk, 2024). The benefits of digitalization extend beyond enhancing security, as it also enables the automation of numerous tasks previously performed manually. This automation is of significant importance, as it reduces the probability of human errors and, more critically, limits the scope of discretionary decisions that are often exploited in corrupt practices (Ponomareva et al., 2021). The primary objective of these digital enhancements is to promote higher levels of openness, transparency, and public oversight in governmental performance. These attributes constitute fundamental pillars in the collective efforts to curb corruption and foster a more integrity-driven and ethical financial environment (Vorontsov et al., 2021).

Financial inclusion, which entails providing affordable financial services to all, is a critical factor in reducing corruption through several key mechanisms. Among the most prominent of these is the enhancement of transparency in financial transactions and the reduction of reliance on cash-based economies. Digital financial transactions are more traceable, making it more challenging to conceal illicit activities and easier to detect them. This positive impact on combating corruption has been observed in various regions and economic contexts, including African countries and middle-income nations, where a clear correlation is noted between increased access to formal banking services and the widespread adoption of digital payment systems on one hand, and a decline in both perceived and actual levels of corruption on the other (Barik and Lenka, 2023; Ajide, 2020; Jungo et al., 2023; Malatyinszki et al., 2025).

Evidence indicates that corruption manifests in various forms, with the embezzlement of public funds being one of the most prominent (Juntunen et al., 2023). Deliberate manipulation of financial data is also one of the most prominent forms of corruption, as it is used to conceal violations or to achieve illicit gains (Nanang et al., 2022). Another form of corruption is the lack of transparency in the management of financial resources, which complicates the processes of oversight and accountability, thereby creating opportunities for misuse and institutional corruption (Maliarchuk, 2024). Such practices not only undermine individuals' trust in banks and financial institutions but also exacerbate the harm inflicted on vulnerable groups more than others. Marginalized individuals often face difficulties in accessing basic financial services, which perpetuates poverty and deepens social and economic disparities. Conversely, financial inclusion is increasingly regarded as a pivotal tool for combating poverty and inequality, promoting social integration, and improving the overall level of social and economic well-being for disadvantaged households (Pripoaie et al., 2024).

Nevertheless, the impact of financial inclusion on corruption is not always direct or evident. In upper-middle-income countries, the effect of financial inclusion may not significantly reduce corruption unless it reaches advanced levels. In lower-middle-income countries and African nations, financial inclusion contributes to reducing corruption to a certain extent. However, excessive expansion, particularly in environments with weak institutions, may lead to unintended consequences and complicate efforts to combat corruption (Barik and Lenka, 2023; Ajide, 2020).

The structure of the article is as follows. Section 1 provides an introduction to the research with particular attention to the relationship between financial inclusion, digitalization, and corruption. Section 2 presents a review of the relevant literature. Section 3 describes the data sources and the methodological approach employed in the analysis. Section 4 reports the empirical results, while Section 5 offers a discussion and interpretation of the findings. Finally, Section 6 summarizes the main conclusions and outlines key policy implications.

2. LITERATURE REVIEW

Corruption has long been regarded as a key impediment to economic growth, institutional trust, and good governance. In recent years, many studies have looked into the socioeconomic determinants of corruption, focusing on things like income levels, banking systems, and employment, these include:

(Ajide, 2020) who examines the impact of financial inclusion on corruption control in 13 African countries between 2005 and 2016. The results reveal a significant positive relationship: a 1% increase in financial inclusion corresponds to a 1.065% improvement in corruption control. However, the study sets a threshold beyond which financial inclusion can be counterproductive in weak institutional environments, potentially encouraging corruption.

(Barik and Lenka, 2023) assess how financial inclusion affects corruption levels in 31 upper- and lower-middle-income countries over the period 2004-2018. Their analysis shows that expanding access to formal financial systems contributes to reducing corruption. However, the effectiveness of this relationship depends on the quality of institutions and the depth of financial inclusion.

(Hasan and Lu, 2023) examine the impact of financial inclusion on sustainability and financial stability across 18 Asian countries, utilizing a comprehensive dataset from 3071 banks between 2008 and 2017, demonstrates that broadening access to financial services significantly bolsters banking sector stability and actively supports sustainable development initiative. Beyond its direct impact on financial institutions, financial inclusion also plays a crucial role in poverty alleviation and the reduction of income disparities by facilitating enhanced access to savings mechanisms and credit facilities. This expanded access not only empowers individuals and small businesses but also contributes to overall economic efficiency by fostering a more stable deposit base for financial institutions and reducing their reliance on inherently riskier external financing sources.

In a related vein, (Jungo et al., 2023) have explored the synergistic interplay between financial literacy, innovation, and inclusion in mitigating the adverse effects of corruption on the stability of the banking sector. An analysis encompassing data from 137 countries across multiple continents reveals that corruption demonstrably exacerbates credit risk and undermines the profitability of financial institutions.

(Trabelsi and Fhima, 2025) explore the interplay between financial inclusion and environmental sustainability in 178 emerging and developing economies between 1996 and 2022. The results highlight a trade-off: While financial inclusion stimulates growth, it also accelerates environmental degradation. However, openness to trade and effective anti-corruption measures can offset these negative environmental outcomes.

(Sarma, 2008) proposes a multidimensional index of financial inclusion (IFI) to assess the level of financial inclusion across countries, applying it to 55 countries using three dimensions and 100 countries using two dimensions. The study reveals stark contrasts, with high IFI scores recorded in countries such as Spain and Switzerland, medium scores in France and Malaysia, and low levels in India, Brazil, and Pakistan. In the context of sub-Saharan Africa, (Yakubu and Musah, 2024) find that expanding financial inclusion tends to reduce bank profitability due to high transaction costs and information asymmetries, particularly among low-income groups. Their analysis highlights that although financial inclusion had little impact before 2006, banking sector stability has consistently enhanced profitability. Building on this, (Bashiru et al., 2023) explore the drivers of financial inclusion in the same region, identifying financial globalization, financial literacy, and rural infrastructure as key factors. Although global integration and education promote financial inclusion, economic growth and strong banks alone do not guarantee expanded financial access.

Recent empirical studies highlight the multifaceted relationship between financial technologies, institutional quality, and sustainable development outcomes. (Zaidi et al., 2021) highlight a paradox in OECD countries, showing that while financial inclusion contributes to economic progress, it also increases energy use and carbon emissions, jeopardizing environmental sustainability. In Vietnam, (Haschka et al., 2023) find that although district-level financial development plays a role in shaping firm productivity, its benefits are significantly multiplied when coupled with strong anti-corruption mechanisms, which help reduce inefficiencies. (Akpabio et al., 2024) emphasize the detrimental effects of corruption on the achievement of the SDGs in West Africa, particularly by undermining the positive impact of remittances and reducing public investment in key sectors such as healthcare, while also stifling female political participation. Similarly, (Rokaya Sultana, 2024) explores how fintech innovations and institutional resilience can together reduce income gaps between countries, suggesting that in the absence of comprehensive trade policies, economic openness may widen inequality gaps. Finally, (Tang et al., 2022) warn of the unintended consequences of rapid adoption of digital finance, revealing that mobile payment systems may initially fuel corruption in weakly regulated environments, emphasizing the need for governance reforms to align digital tools with anti-corruption objectives.

3. DATA AND METHODOLOGY

3.1. Data Source

A macroeconomic dataset was used, encompassing MENA countries, representing economic and social indicators such as bank branches, number of ATMs, deposits banks, loans banks[1], GDP per capita, unemployment, inflation, population growth, and personal remittances[2]. In addition to the Corruption Perceptions Index[3] (a high score indicates low corruption). Data were collected from open and reliable databases such as the World Bank, IMF, and International Transparency Organization from 2004 to 2023.

Missing values (represented by "...") were processed and converted. Variables were also normalized using the MinMaxScaler to facilitate learning in deep models.

3.2. Methodology

The following models were trained:

- Linear regression: A simple linear model to determine the relationship between independent and dependent variables.
- Random forest: A robust ensemble model based on multiple decision trees.
- RNN, LSTM, and Attention-RNN: Sequential models that use deep neural architectures to learn complex relationships in data.

The data was split into two sets:

- 80% for training.
- 20% for testing.

After 100 epochs of training being used for the deep models, the results below show the training percentages:

- RNN: 99.30%
- LSTM: 98.58%
- Attention-RNN: 98.81%
- Random forest: 99.41%
- Linear Regression: 99.09

The data presented demonstrates the performance of various deep learning models, including Recurrent Neural Networks (RNNs) and other algorithms such as Random Forest and Linear Regression. The percentages likely represent the accuracy of each model on a prediction task. The results indicate that Random Forest achieved the highest accuracy in this particular scenario.

Deep models showed good stability during training, with a clear improvement when the attention mechanism was introduced into the Attention-RNN, indicating its role in capturing nonlinear patterns and indirect temporal relationships.

1 https://data.imf.org/en/datasets/IMF.STA:FAS
2 https://databank.worldbank.org/source/world-development-indicators
3 https://www.transparency.org/en/cpi/

4. RESULTS AND DISCUSSION

4.1. Evaluation of the Models

The models were evaluated using the following metrics:

- Mean squared error (MSE)
- Root mean squared error (RMSE)
- Mean absolute error (MAE)
- Coefficient of determination (R^2)

The figure 1 below presents the performance metrics of different deep learning models: MSE (mean squared error), RMSE (root mean squared error), and MAE (mean absolute error) which measure the error between predicted and actual values. Lower values are generally better.

R^2 (R-squared) represents the coefficient of determination, indicating the proportion of variance in the dependent variable that can be predicted from the independent variables. Higher values (closer to 1) are better.

The figure 1 compares the performance of various deep learning models (RNN, LSTM, Attention-RNN, Random Forest, and Linear Regression) based on their ability to predict a certain outcome. The metrics provide a quantitative way to assess and compare the accuracy of each model. The lower the error metrics (MSE, RMSE, MAE) and the higher the R-squared value, the better the model's performance.

Based on the figure, we note that the Random Forest model is the best in terms of performance (highest R^2 value and lowest MSE), followed by the RNN model.

4.2. Linear Regression Model Analysis

In the analysis of the provided regression results, various economic indicators were examined to understand their relationships with financial metrics. The Table 1 presents coefficients, P-values, significance levels, and confidence intervals for each feature.

All examined variables, including bank branches, number of ATMs, outstanding loans, GDP per capita, unemployment, and personal remittances, show statistically significant positive relationships with the Corruption Perceptions Index, meaning that higher values of these factors are associated with a higher corruption index, meaning less corruption is prevalent.

However, the negative coefficient for outstanding deposits with commercial banks (% of GDP) indicates that higher outstanding deposits are associated with lower CPI. The strong significance indicates the strength of this relationship. The negative coefficient also of inflation indicates that higher rates are associated with lower CPIs. These important results highlight the negative effects of inflation on the prevalence of corruption.

In addition to the aforementioned, the population growth variable's positive and statistically insignificant coefficient suggests that it has no discernible impact on the dependent variable in this situation.

Figure 1: Evaluation results

Model	MSE	RMSE	MAE	R^2
RNN	0.007040	0.083905	0.068741	0.825182
LSTM	0.014234	0.119307	0.099724	0.646540
Attention-RNN	0.011919	0.109172	0.092730	0.704038
Random Forest	0.005909	0.076870	0.053345	0.853269
Linear Regression	0.009109	0.095443	0.081787	0.773796

Source: Author's calculations

4.3. Analysis of Variables in Other Models

The tables provides an overview of key financial and economic indicators, such as the number of bank branches and ATMs, outstanding deposits and loans, per capita GDP, unemployment, inflation, population growth, and personal remittances. These metrics are often used to assess a country's economic health and financial development. The "Importance (%)" and "Standard Deviation" columns indicate the statistical analysis of the four model, where the importance of each factor is assessed.

- Importance (%) reflects the extent to which a variable influences the model's predictions.
- Higher values indicate variables with a greater influence on the Corruption Perception Index.
- Std shows the variation in importance estimates across replicates.

4.3.1. RNN model analysis

Looking at this features importance table through a different analytical lens, here's what the data reveals (Table 2):

Outstanding loans (25.16%) and Outstanding deposits (22.45%) together control nearly half of all predictive power, indicating that the actual flow of money through banks—not just their presence—drives the corruption index.

Table 1: Linear regression outputs

Features	Coefficient	P-value	Significant (P<0.05)	95% CI lower	95% CI upper
Number of commercial bank branches per 100,000 adults	0.2013	0.0000	Yes	0.1263	0.2764
Number of ATMs/100,000 adults	0.1928	0.0000	Yes	0.1076	0.2779
Outstanding deposits with commercial banks (% of GDP)	−0.5466	0.0000	Yes	−0.6581	−0.4351
Outstanding loans from commercial banks (% of GDP)	0.5442	0.0000	Yes	0.4071	0.6812
GDP per capita (constant 2015 US$)	0.4165	0.0000	Yes	0.3134	0.5196
Unemployment, total (% of total labor force) (modeled ILO estimate)	0.0968	0.0248	Yes	0.0124	0.1812
Inflation, consumer prices (annual %)	−0.5138	0.0000	Yes	−0.7205	−0.3071
Population growth (annual %)	0.0806	0.3305	No	−0.0823	0.2434
Personal remittances, received (% of GDP)	0.3488	0.0000	Yes	0.2101	0.4875

Source: Author's calculations

GDP per capita serves as the economic bedrock, but notably doesn't dominate as much as one might expect in economic models, suggesting this analysis focuses specifically on banking sector dynamics rather than general economic performance.

Physical infrastructure (branches + ATMs): 8.97%

The remaining variables—unemployment, inflation, population growth, and remittances—collectively contribute about 11%, functioning as contextual modifiers rather than primary drivers. This suggests the model captures banking sector performance independent of broader macroeconomic volatility.

4.3.2. LSTM model analysis

Looking at this features importance table, several key insights emerge about the factors driving the model's predictions (Table 3):

4.3.2.1. Most important factors

GDP per capita (39.94%) is the most influential variable in the corruption perceptions index, accounting for nearly 40% of the model's predictive power. This means that any outcome, most likely financial inclusion, is primarily determined by a country's overall economic prosperity.

The number of ATMs per 100,000 adults (20.85%) is the second most important factor, suggesting that access to financial infrastructure plays a crucial role. This makes sense, as the availability of ATMs directly impacts people's access to banking services.

4.3.2.2. Moderate impact

Outstanding loans from commercial banks (14.67%) shows that credit availability and lending activity significantly influence the corruption, indicating the importance of active financial intermediation. Outstanding deposits (10.30%) and the number of bank branches per 100,000 adults (7.41%) contribute significantly, reinforcing the importance of banking infrastructure and deposit flows in the severity of corruption.

4.3.2.3. Surprising result

Unemployment (−0.26%) showed a slightly negative significance, which is unusual. This may indicate either that unemployment has an unexpected relationship with the corruption, or that once other economic factors are controlled, the direct effect of unemployment becomes insignificant or even slightly negative.

4.3.2.4. Little impact

Inflation (3.94%), population growth (1.93%), and personal remittances (0.70%) have relatively low significance, suggesting that these factors are less important for corruption when accounting for key economic and infrastructure variables.

4.3.3. Attention-RNN model analysis

An analysis of the importance of attributes reveals a hierarchical structure in the determinants of corruption, with GDP per capita (30.8852%) serving as the most influential factor, confirming the central role of economic output per capita in analyzing corruption (Table 4). Outstanding deposits with commercial banks (23.7830%) emerge as the second most important attribute, indicating that deposit levels significantly influence perceptions of corruption, followed by outstanding loans from commercial banks (16.2231%), reflecting the importance of lending activities in the model. Availability of ATMs (15.7017%) shows greater importance than bank branches (4.7879%), highlighting that access to automated financial services plays a more significant role than

Table 2: Features Importance Analysis in RNN model

Features	Importance (%)	Std
Number of commercial bank branches per 100,000 adults	3.4332	0.0005
Number of ATMs/100,000 adults	5.5414	0.0011
Outstanding deposits with commercial banks (% of GDP)	22.4493	0.0022
Outstanding loans from commercial banks (% of GDP)	25.1596	0.0032
GDP per capita (constant 2015 US$)	32.3886	0.0036
Unemployment, total (% of total labor force) (modeled ILO estimate)	2.5134	0.0008
Inflation, consumer prices (annual %)	2.4671	0.0006
Population growth (annual %)	0.1230	0.0001
Personal remittances, received (% of GDP)	5.9242	0.0010

Source: Author's calculations

Table 3: Features Importance Analysis in LSTM model

Features	Importance (%)	Std
Number of commercial bank branches per 100,000 adults	7.4117	0.0007
Number of ATMs per 100,000 adults	20.8526	0.0015
Outstanding deposits with commercial banks (% of GDP)	10.3025	0.0007
Outstanding loans from commercial banks (% of GDP)	14.6661	0.0016
GDP per capita (constant 2015 US$)	39.9367	0.0023
Unemployment, total (% of total labor force) (modeled ILO estimate)	−0.2556	0.0002
Inflation, consumer prices (annual %)	3.9429	0.0004
Population growth (annual %)	1.9333	0.0003
Personal remittances, received (% of GDP)	0.6987	0.0001

Source: Author's calculations

Table 4: Features importance analysis in attention-RNN model

Features	Importance (%)	Std
Number of commercial bank branches per 100,000 adults	4.7879	0.0007
Number of ATMs per 100,000 adults	15.7017	0.0017
Outstanding deposits with commercial banks (% of GDP)	23.7830	0.0019
Outstanding loans from commercial banks (% of GDP)	16.2231	0.0022
GDP per capita (constant 2015 US$)	30.8852	0.0026
Unemployment, total (% of total labor force) (modeled ILO estimate)	1.4111	0.0004
Inflation, consumer prices (annual %)	4.2181	0.0007
Population growth (annual %)	0.9455	0.0002
Personal remittances, received (% of GDP)	2.0444	0.0007

Source: Author's calculations

traditional branch infrastructure in the dynamics of corruption. The remaining variables exhibit a medium to small effect: inflation (4.2181%) has a moderate effect, personal remittances (2.0444%) and unemployment (1.4111%) exhibit limited effects, while population growth (0.9455%) is less significant, indicating a negligible effect on the CPI. This pattern suggests that economic prosperity and banking sector activity are the primary drivers of corruption perceptions, while demographic and labor market factors play secondary roles.

4.3.4. Random forest model analysis

According to the attribute importance analysis, the main factor influencing corruption perceptions is GDP per capita (64.6933%, standard deviation: 0.0083), which outweighs all other factors (Table 5). This shows a clear hierarchy of dominance in the determinants of corruption perceptions. Outstanding commercial bank loans as a percentage of GDP comes in second (11.4881%, standard deviation: 0.0012), followed by unemployment rates (9.2001%, standard deviation: 0.0016), indicating that labor market conditions and credit availability have a significant impact on corruption dynamics. Remittance is next with a value of (5.0820%, standard deviation: 0.0011), and then Deposit, indicating that the impact of financial inclusion on corruption perceptions is (11.4881+2.9081).While banking infrastructure variables show a similar and surprisingly small impact such as: commercial bank branches (2.7708%, SD: 0.0005), and ATMs (2.7260%, SD: 0.0010), suggesting that banking access points have a limited impact on perceptions of corruption. Inflation and population growth have the lowest levels of significance (0.2105%, SD: 0.0000 and 0.9211%, SD: 0.0001), with inflation having a very small impact on the CPI.

Financial inclusion improves access to formal financial services, hence diminishing informal cash transactions that are susceptible to corruption. Digitization increases transparency and augments transaction traceability, hence complicating efforts to obscure corruption, which serves as an impediment when bureaucracy and opaque processes are employed to marginalize sectors of the population or distort data.

Table 5: Features importance analysis in random forest model

Features	Importance (%)	Std
Number of commercial bank branches per 100,000 adults	2.7708	0.0005
Number of ATMs per 100,000 adults	2.7260	0.0010
Outstanding deposits with commercial banks (% of GDP)	2.9081	0.0002
Outstanding loans from commercial banks (% of GDP)	11.4881	0.0012
GDP per capita (constant 2015 US$)	64.6933	0.0083
Unemployment, total (% of total labor force) (modeled ILO estimate)	9.2001	0.0016
Inflation, consumer prices (annual %)	0.2105	0.0000
Population growth (annual %)	0.9211	0.0001
Personal remittances, received (% of GDP)	5.0820	0.0011

Source: Author's calculations

Based on the literature study and empirical evidence, digitalization and financial inclusion are effective instruments for decreasing corruption and boosting economic growth. Their performance is determined by financial education levels, the quality of digital infrastructure, and cautious risk management, such as over-indebtedness and persistent socioeconomic disparities. Expanding digital financial services, particularly when combined with education and adequate infrastructure, can considerably improve transparency and financial access, but it must be done carefully to avoid unanticipated negative outcomes.

5. CONCLUSION

The regression analysis provides valuable insights into the relationships between various financial and economic indicators and their impact on corruption metrics. The significant variables, such as the number of bank branches, ATMs, outstanding loans, GDP per capita, unemployment, and personal remittances, highlight the importance of financial accessibility and economic health. Conversely, outstanding deposits and inflation demonstrate negative impacts, emphasizing the complexities of economic interactions. Understanding these relationships can aid policymakers and economists in making informed decisions to foster economic growth and stability.

The results of (RNN, LSTM, Attention-RNN and random forest) suggest that the models are primarily driven by economic prosperity (GDP per capita) and active banking sector activity (loans, deposits), with financial infrastructure availability (ATMs, bank branches) playing supporting roles. This pattern would be consistent with models predicting financial inclusion.

The dataset provides a comprehensive overview of various economic and financial indicators. The analysis reveals the relative importance of each feature, with GDP per capita showing the highest impact. The standard deviation values offer insights into the variability associated with each feature. This objective interpretation provides a foundation for further analysis and understanding of the relationships between these economic and financial variables.

Financial inclusion is an effective instrument for eliminating corruption, particularly when combined with digital payment systems, and strong institutions. However, its efficiency is dependent on striking the proper balance and ensuring strong governance. Excessive or poorly managed financial inclusion in underdeveloped institutional environments may reduce or even reverse its anti-corruption effects.

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