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The Impact of Artificial Intelligence and Digitalization on the Foreign Exchange Market

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Abstract This study investigates the impact of artificial intelligence capability and digitalization on foreign exchange (FX) market performance in Malaysia over the period 2015–2024. Using the MYR/USD exchange rate, the analysis focuses on three key dimensions: volatility persistence, price discovery efficiency, and market resilience and stability. The full sample consists of 10 annual observations and a quantitative time-series framework is employed, integrating econometric modeling with machine-learning validation techniques. The results from baseline regression models indicate that both artificial intelligence capability and digitalization are significantly associated with lower volatility persistence, higher price discovery efficiency, and stronger market resilience. The interaction between these variables shows a strong complementary association, suggesting that digital infrastructure amplifies the benefits of AI in financial markets. Robustness checks using LASSO and Random Forest confirm the consistency of these findings. Additionally, Diebold–Mariano tests reveal no significant differences in predictive performance across models. The study contributes by integrating AI capability and digitalization into a unified FX-market framework and by showing that technological complementarity is associated with market efficiency, stability, and adaptive capacity in an emerging-market context.

Keywords Artificial Intelligence Capability; Digitalization; Exchange Rate Volatility; Predictive Modeling; Market Stability.

AMS 2010 subject classifications 62M10, 68T10

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1. Introduction

The foreign exchange (FX) market plays a central role in the global financial system because it supports international trade, cross-border investment, capital mobility, monetary policy transmission, and macroeconomic stability. Exchange rate movements are closely linked with financial uncertainty, trade competitiveness, inflationary pressure, and investor expectations. Because of this, understanding the factors that influence FX market behavior is important for policymakers, investors, central banks, and financial institutions.

Exchange rates often exhibit volatility clustering, where periods of high volatility tend to be followed by further periods of instability [1]. This makes exchange rate behavior difficult to predict, especially during periods of global financial stress. In addition, exchange rate series frequently show nonlinear adjustment and regime-dependent movement, which limits the explanatory power of simple linear models [2]. These challenges are more serious in emerging markets because their currencies are often more sensitive to external shocks, capital-flow reversals, and changes in global risk sentiment [3].

Recent technological transformation has created new technological trends in financial markets. Artificial intelligence (AI) has become increasingly important because it is associated with stronger forecasting, information

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processing, pattern recognition, and data-driven financial decision-making [4]. Machine-learning models are especially useful in financial time-series analysis because they can capture hidden nonlinear relationships that traditional econometric models may fail to detect [5]. Digitalization has also changed financial-market operations by improving electronic trading, digital connectivity, market transparency, and real-time information transmission [6].

In FX markets, where prices respond rapidly to news, expectations, and global shocks, AI capability and digital infrastructure may be associated with the efficiency of information incorporation into exchange rates. Digital financial systems are associated with lower transaction frictions and faster market adjustment [7]. Similarly, AI-supported trading and forecasting tools may be associated with stronger market responsiveness, particularly when large volumes of information are processed more quickly than conventional methods [8]. Therefore, AI capability and digitalization may be associated with key FX market outcomes, including volatility persistence, price discovery efficiency, and market resilience.

Although exchange rate volatility and market efficiency have been widely studied, the role of technological transformation in FX market performance remains underexplored. Much of the existing literature focuses on macroeconomic fundamentals, financial openness, interest rate differentials, and global risk conditions as correlates of exchange rate behavior. However, the increasing use of AI, digital platforms, algorithmic trading, and real-time data systems suggests that technology may now play a more direct role in shaping FX market outcomes.

Prior studies have examined AI and machine learning mainly from the perspective of forecasting performance rather than FX market behavior [9]. Other studies have investigated digital finance and financial technology, but they often focus on banking, payment systems, or financial inclusion rather than exchange rate efficiency and resilience [10]. As a result, limited empirical evidence exists on how AI capability and digitalization jointly are associated with FX market outcomes within a single analytical framework.

Another important research gap is that most existing studies focus on only one dimension of FX market performance, such as volatility or forecasting accuracy. However, FX market performance is multidimensional and should be evaluated through volatility persistence, price discovery efficiency, and market resilience. Volatility persistence reflects how long exchange rate shocks remain in the market. Price discovery efficiency shows how quickly and accurately new information is reflected in exchange rates. Market resilience indicates the ability of the FX market to absorb shocks and return to stable conditions.

The emerging-market context also remains insufficiently examined. Emerging markets are often more exposed to global financial shocks and financial-market vulnerabilities than advanced economies [11]. Malaysia provides a relevant case because it has experienced rapid digital transformation while remaining exposed to global capital flows, exchange rate pressure, and external financial uncertainty. Therefore, this study addresses the gap by examining whether AI capability and digitalization are associated with the efficiency, stability, and adaptive capacity of the MYR/USD exchange rate market.

The main objective of this study is to examine the associations between artificial intelligence capability, digitalization, and foreign exchange market outcomes in Malaysia, specifically volatility persistence, price discovery efficiency, and market resilience, and to validate the robustness of the empirical findings using machine-learning approaches. This study contributes to the literature by incorporating AI capability and digitalization as technological correlates of FX market performance, providing emerging-market evidence from Malaysia, and combining econometric analysis with machine-learning validation using LASSO and Random Forest [12].

The findings show that AI capability and digitalization are associated with lower volatility persistence, higher price discovery efficiency, and stronger market resilience in the MYR/USD market. The interaction term suggests that digital infrastructure conditions the association between AI and FX-market outcomes. The machine-learning validation results further confirm that the findings are stable and not dependent on a single model specification.

The remainder of this paper is organized as follows. Section 2 reviews the related literature on AI capability, digitalization, and FX market performance. Section 3 presents the conceptual framework and develops the study hypotheses. Section 4 explains the methodology, variable measurement, model specifications, diagnostic tests, and robustness procedures. Section 5 reports the empirical analysis and results. Section 6 discusses the findings in relation to the theoretical and empirical literature. Section 7 presents the policy and managerial implications, while Section 8 outlines directions for future research. Finally, Section 9 concludes the paper. “‘

2. Literature Review

This section reviews the theoretical and empirical foundations linking artificial intelligence capability, digitalization, and foreign exchange market performance. The discussion is organized around AI-related financial markets, digital infrastructure, volatility dynamics, price discovery, and market resilience, followed by a synthesis of the key research gaps addressed in this study.

2.1. *Theoretical Perspectives on AI-Related Financial Markets*

The theoretical foundation of this study is grounded in market microstructure theory, adaptive market theory, and financial innovation-endogenous risk theory. Market microstructure theory explains how trading mechanisms, liquidity, information flow, and order execution influence price formation in financial markets [13]. In FX markets, exchange rates are shaped not only by macroeconomic fundamentals but also by how quickly market participants process and respond to information [14]. Therefore, AI capability and digitalization may be associated with stronger market decision-making through faster and more accurate information processing.

Adaptive market theory suggests that financial markets evolve as participants learn from changing conditions and adjust their strategies over time [15]. In this context, AI can be associated with market adaptation through nonlinear-pattern identification, risk detection, and forecasting under uncertainty [16]. Digitalization is also associated with adaptation through stronger data access, market connectivity, and real-time information transmission [17].

Financial innovation-endogenous risk theory provides a combined explanation of how technological progress is associated with market functioning as well as risks generated within the financial system. AI and digitalization represent financial innovations that may be associated with liquidity, lower transaction frictions, higher price discovery, and stronger risk monitoring [18]. At the same time, technology-supported trading may be linked with endogenous risk through similar algorithmic responses, herding behavior, or rapid liquidity withdrawal during unstable periods [19].

Overall, these theories support the argument that AI capability and digitalization can reshape FX market behavior by improving information processing, market adaptation, innovation, and risk management. Therefore, this study argues that AI capability and digitalization are expected to be associated with lower volatility persistence, higher price discovery efficiency, and stronger market resilience in FX markets [20].

2.2. *AI Capability and Algorithmic Intelligence in FX Trading*

Artificial intelligence has become an important tool in financial market analysis because it supports forecasting, classification, risk assessment, and automated decision-making. Machine-learning techniques are useful in FX markets because exchange rate movements often involve nonlinear relationships, time-varying dependencies, and hidden structures that traditional models may not fully capture [21]. Deep-learning models further improve financial forecasting by identifying sequential patterns and complex temporal relationships in financial data [22].

In FX trading, algorithmic intelligence allows market participants to process large volumes of macroeconomic, financial, and market-sentiment data more quickly. AI-based systems can detect abnormal price movements, identify trading signals, and improve risk-adjusted decision-making [23]. These capabilities are highly relevant in FX markets, where exchange rates respond rapidly to monetary policy expectations, global shocks, and investor sentiment [24]. Therefore, stronger AI capability may be associated with lower information delays and faster exchange-rate adjustment.

Hybrid AI models have also received growing attention because they combine the strengths of different modeling approaches. These methods may improve predictive accuracy, reduce model instability, and capture complex market behavior more effectively [25]. In this study, AI capability is not treated only as a forecasting tool but also as a technological correlate of FX market performance. Stronger AI capability is expected to be associated with lower volatility persistence, higher price discovery efficiency, and stronger market resilience.

2.3. Digitalization and Electronic Market Infrastructure

Digitalization has transformed financial markets through electronic trading systems, digital connectivity, data-processing capacity, and real-time access to information. Electronic trading platforms are associated with lower transaction costs and faster financial-market operations [26]. In FX markets, faster trading infrastructure is associated with liquidity, fewer delays, and faster price adjustment [27].

Digital financial development is also associated with greater transparency and broader access to financial services. Stronger digital infrastructure allows market participants to receive information more quickly and execute transactions more efficiently [28]. This is associated with lower informational frictions and better coordination among market participants [29]. In emerging markets, digitalization may be especially important because it is linked with financial-market access and institutional efficiency.

Digitalization also provides the foundation for AI-based financial applications. AI systems require reliable data, computational capacity, digital platforms, and real-time connectivity to operate effectively [30]. Therefore, digitalization may be associated with FX market performance and may condition the association between AI capability and FX market outcomes. This supports the inclusion of the AI capability and digitalization interaction term in the empirical framework.

2.4. AI, Digitalization, and FX Market Volatility Dynamics

Volatility persistence is a major concern in FX markets because it reflects how long exchange rate shocks remain after they occur. Persistent volatility increases uncertainty, is relevant to hedging decisions, and may weaken financial stability [31]. Previous studies show that exchange rate volatility often clusters over time, meaning that large fluctuations are likely to be followed by further instability [32]. This pattern is particularly important in emerging markets, where currencies are more sensitive to external shocks and capital-flow movements.

AI capability may be associated with lower volatility persistence through stronger forecasting accuracy and faster identification of abnormal market conditions [33]. When market participants process information more efficiently, exchange rates may adjust more quickly to new signals, reducing the duration of volatility shocks. Digitalization may also be associated with lower volatility persistence by improving market connectivity and accelerating the transmission of information across trading platforms [34].

The joint association of AI and digitalization may be stronger than their separate associations. AI tools depend on digital infrastructure for real-time data access, computational power, and platform integration [35]. Therefore, stronger digitalization can be linked with a stronger ability of AI systems to detect market changes and support faster adjustment. This study therefore expects AI capability, digitalization, and their interaction to be associated with lower volatility persistence in the MYR/USD market.

2.5. AI-Associated Price Discovery and Informational Efficiency

Price discovery refers to the process through which new information is incorporated into market prices. In efficient FX markets, exchange rates should respond quickly and accurately to macroeconomic news, monetary policy changes, and global financial developments [36]. However, informational frictions, weak transparency, and asymmetric access to data can delay market adjustment [37].

AI-supported systems can be associated with higher price discovery when large and complex datasets are processed more quickly than conventional methods. Machine-learning models can detect nonlinear signals, market sentiment, and hidden relationships that may be associated with exchange rate movements [38]. As a result, AI capability may be associated with greater speed and accuracy with which information is reflected in exchange rates.

Digitalization also supports price discovery by increasing the speed of information transmission and reducing transaction delays. Electronic platforms and real-time data networks allow market participants to respond more quickly to new information [39]. When AI capability operates within a strong digital environment, price adjustment may become faster and more efficient. Therefore, this study expects AI capability and digitalization to be associated with higher price discovery efficiency in the Malaysian FX market.

2.6. Digital Resilience and Stability in Foreign Exchange Markets

Market resilience refers to the ability of a financial market to absorb shocks and return to stable conditions without prolonged disruption. In FX markets, resilience is important because exchange rates are exposed to global uncertainty, policy shocks, capital-flow volatility, and speculative pressure [40]. Regime-switching behavior in exchange rates shows that currencies may move between stable and unstable periods depending on market conditions [41].

Digitalization can be associated with stronger market resilience by improving operational efficiency, transaction continuity, market monitoring, and information availability [42]. A more digital financial system allows market participants and institutions to respond faster during periods of stress. It can also support better risk management by providing timely information about liquidity, volatility, and market pressure.

AI capability may be associated with resilience through early warning signals, stress-pattern identification, and adaptive decision-making [43]. When AI systems are supported by strong digital infrastructure, the FX market may become more responsive and stable. Therefore, AI capability and digitalization are expected to be associated with stronger market resilience and stability, particularly when they operate together.

2.7. Synthesis of Empirical Evidence and Research Gaps

The reviewed literature shows that exchange rate dynamics are influenced by macroeconomic fundamentals, global financial conditions, market structure, and technological change [44]. Prior studies confirm that FX markets often display volatility clustering, nonlinear behavior, and regime-dependent adjustment. The literature also shows that AI and machine-learning models can be associated with stronger forecasting by capturing complex nonlinear patterns in financial time series [45]. In addition, digitalization is associated with financial connectivity, market access, and information transmission [46].

Despite these contributions, several research gaps remain. First, many studies examine AI, digitalization, or exchange rate behavior separately rather than integrating them into one FX market framework. Second, prior studies often focus on forecasting accuracy but give less attention to FX market outcomes such as volatility persistence, price discovery efficiency, and market resilience. Third, emerging-market evidence remains limited, although emerging FX markets are more exposed to external shocks and may benefit differently from technological transformation. Finally, limited attention has been given to the interaction between AI capability and digitalization, even though AI systems depend heavily on digital infrastructure.

This study addresses these gaps by examining the associations between AI capability, digitalization, and Malaysia's FX market outcomes using the MYR/USD exchange rate. The study focuses on volatility persistence, price discovery efficiency, and market resilience, and validates the findings using machine-learning approaches. Therefore, the literature supports the central argument that AI-related digital transformation may be associated with FX market efficiency, stability, and adaptive capacity in an emerging-market context.

3. Conceptual Framework

The conceptual framework of this study is theoretically grounded in market microstructure theory, adaptive market theory, and financial innovation–endogenous risk theory. These theories suggest that FX market outcomes are associated with trading mechanisms, information flow, market connectivity, technological innovation, and internally generated financial risk [13, 14, 15]. Since global FX markets operate with very high trading intensity, technological capacity has become increasingly important for information processing and market adjustment. For example, the Bank for International Settlements reported that global FX turnover reached about USD 7.5 trillion per day in 2022.

This study develops a conceptual framework to explain how AI capability and digitalization are associated with foreign exchange market outcomes. AI capability may be associated with stronger forecasting accuracy, signal detection, risk monitoring, and adaptive decision-making, while digitalization is associated with real-time information transmission, electronic trading infrastructure, and market connectivity [16, 17]. Recent OECD evidence also shows that AI is increasingly used in finance for risk management, fraud detection, compliance, portfolio management, and trading-related activities, supporting its relevance for financial-market efficiency.

Artificial intelligence capability is treated as a key technological correlate of FX market performance. Higher AI capability can help market participants identify abnormal exchange-rate movements, process new information more efficiently, and respond faster to global shocks and policy signals. Therefore, AI capability is expected to be associated with lower volatility persistence, higher price discovery efficiency, and stronger market resilience and stability [18]. However, recent financial-stability discussions also note that AI may create new vulnerabilities if automated systems produce similar responses or amplify market feedback associations.

Digitalization is also expected to be associated with FX market outcomes through stronger connectivity, faster information transmission, lower transaction frictions, and better electronic market infrastructure. A more digitalized financial system allows investors, banks, and financial institutions to access and process information in real time, which is consistent with faster exchange-rate adjustment and more efficient market responses [19]. Thus, digitalization is expected to be associated with higher FX market efficiency, lower prolonged volatility, and stronger market stability.

The framework also considers the interaction between AI capability and digitalization. AI systems require reliable data, digital infrastructure, computational capacity, and strong connectivity to function effectively. Therefore, the association between AI capability and FX market outcomes may be stronger in economies with higher levels of digitalization. This interaction reflects technological complementarity, where digitalization conditions the association between AI and FX market efficiency and resilience [20].

To isolate the association of technological factors, the framework includes global risk conditions, financial openness, and interest rate differential as control variables. These controls capture external uncertainty, capital-market integration, and monetary-policy-related exchange-rate pressure. Based on this conceptual logic, the proposed research framework is presented in Figure 1.

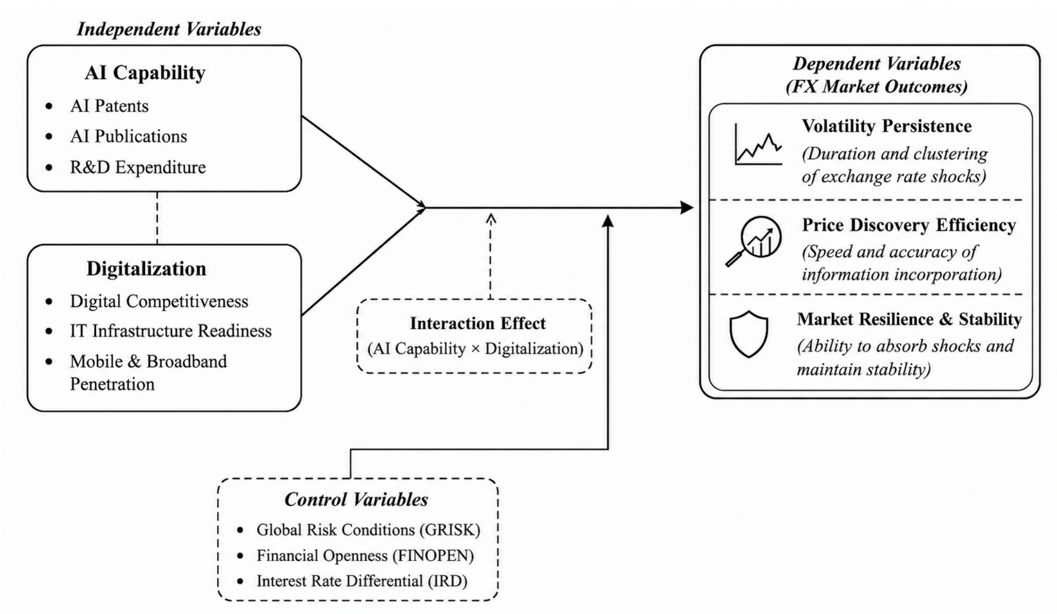

Figure 1. Conceptual framework of AI capability, digitalization, and FX market outcomes

Based on market microstructure theory, adaptive market theory, and financial innovation theory, this study proposes that AI capability and digitalization are associated with stronger FX-market performance through stronger information processing, digital connectivity, and market adjustment. Accordingly, the following hypotheses are developed:

- **H1:** AI capability, digitalization, and their interaction are negatively associated with volatility persistence in the FX market.
- **H2:** AI capability, digitalization, and their interaction are positively associated with price discovery efficiency in the FX market.
- **H3:** AI capability, digitalization, and their interaction are positively associated with Market Resilience & Stability in the FX market.

4. Methodology

This study adopts a quantitative time-series research design to examine the association between artificial intelligence capability, digitalization, and foreign exchange market performance in Malaysia. The analysis focuses on the MYR/USD exchange rate over the period 2015–2024. Malaysia is selected because it represents an emerging market with increasing digital transformation, growing AI-related capacity, and strong exposure to global financial and exchange-rate movements. The MYR/USD exchange rate is used because the US dollar is the dominant international currency for trade, investment, and financial transactions, making it highly relevant for evaluating Malaysia's FX market behavior.

The period 2015–2024 is selected because this period captures important changes in Malaysia's digital infrastructure, AI development, and financial technology environment. It includes several episodes of global uncertainty, including post-2015 exchange-rate pressures, the COVID-19 period, and the post-pandemic global monetary tightening period. In addition, reliable and comparable data for AI capability, digitalization, macro-financial variables, and exchange-rate indicators are more consistently available for this period. The final sample therefore consists of 10 annual observations. Although the sample size is relatively small, it is appropriate for an exploratory time-series association study where the independent variables, such as AI capability and digitalization, change gradually over time. To reduce overfitting concerns, this study uses a parsimonious model, lagged explanatory variables, diagnostic tests, and machine-learning validation as robustness checks.

The data are collected from several secondary sources and organized at an annual frequency for the period 2015–2024. The MYR/USD exchange rate is obtained from international financial databases such as the IMF International Financial Statistics, Bank Negara Malaysia, or World Bank databases. Where higher-frequency exchange-rate observations are available, they are converted into annual measures to ensure consistency with the annual technology and macro-financial indicators. AI capability is constructed using AI-related patent applications, AI-related scientific publications, and AI-related research and development indicators from sources such as WIPO, OECD.AI, Scopus/Web of Science, and World Bank data. Digitalization is measured using digital competitiveness, ICT infrastructure, broadband penetration, and mobile connectivity indicators from sources such as the World Bank, ITU, IMD, and national digital economy reports. Global risk conditions are proxied by the VIX index, while financial openness is measured using the Chinn–Ito capital account openness index. The interest rate differential is calculated using Malaysia's short-term interest rate and the corresponding US benchmark rate.

This study acknowledges that financial-sector-specific AI capability data would provide a more direct measure of AI adoption in FX-market activity. However, consistent annual financial-sector AI indicators for Malaysia over 2015–2024 are not publicly available. Accordingly, national-level AI capability is used as a proxy for the broader technological environment that supports financial-market digital transformation. This proxy is appropriate because FX-market efficiency depends not only on AI adoption within banks and trading desks, but also on the wider AI ecosystem, including data infrastructure, skilled human capital, cloud capacity, fintech innovation, and real-time analytical systems. Therefore, national-level AI capability is interpreted as a macro-level enabling condition that may support forecasting, risk monitoring, trading efficiency, and market surveillance, rather than as a direct measure of AI use by individual FX traders.

The variables of this study are classified into dependent, independent, interaction, and control variables. The dependent variables are the three indicators of foreign exchange market performance: volatility persistence (VP), price discovery efficiency (PDE), and market resilience and stability (MRS). The main independent variables are artificial intelligence capability (AIC) and digitalization (DI). AI capability captures the extent to which Malaysia develops and applies AI-related knowledge, innovation, and technological capacity, while digitalization reflects the strength of digital infrastructure, ICT connectivity, and digital market readiness. The study also includes an interaction term, AIC $\times$ DI, to examine whether digitalization conditions the association between AI capability and FX market performance. In addition, global risk conditions, financial openness, and interest rate differential are included as control variables.

4.1. Measurement of Variables

The study evaluates three dependent variables: volatility persistence, price discovery efficiency, and market resilience and stability. Volatility persistence is measured using a GARCH-type framework because exchange-rate returns commonly exhibit volatility clustering, where large shocks are followed by further large movements. The MYR/USD exchange rate is first transformed into continuously compounded returns as:

$$r_t = \ln(S_t) - \ln(S_{t-1}) \tag{1}$$

where S_t denotes the exchange rate of MYR/USD at time t. A GARCH(1,1) model is then estimated, and volatility persistence is calculated as:

$$VP = \alpha + \beta \tag{2}$$

where α captures the short-run shock association and β captures volatility memory. A higher value of VP indicates stronger volatility persistence, while a lower value indicates faster shock absorption.

Price discovery efficiency is measured using a composite index based on the variance ratio approach and the speed of adjustment from a vector error correction model. The variance ratio is used because it evaluates whether exchange-rate returns follow a random-walk process, which is closely related to market efficiency. The VECM speed of adjustment is included because price discovery also depends on how quickly exchange rates correct deviations from equilibrium. The price discovery efficiency index is calculated as:

$$PDE = w_1 VR(k) + w_2 ECS \tag{3}$$

where $VR(k)$ is the variance ratio, ECS is the error-correction speed, and w_1 and w_2 are weights assigned to each component. A higher value of PDE indicates stronger price discovery efficiency.

Market resilience and stability are measured using a two-state Markov-switching model because FX markets often move between low-volatility and high-volatility regimes. This method is appropriate because market resilience is not only about average volatility but also about the probability of remaining in or returning to a stable regime. The resilience measure is calculated as:

$$MRS = 1 - p_t^H \tag{4}$$

where p_t^H is the filtered probability of being in the high-volatility regime. A higher MRS value indicates stronger market resilience and stability.

The main independent variables are Artificial Intelligence Capability (AIC) and the Digitalization Index (DI). Both variables are constructed as composite indices using min–max normalization because the component indicators are measured in different units. The normalization formulas are:

$$X_t^* = \frac{X_t - \min(X)}{\max(X) - \min(X)} \tag{5}$$

$$Y_t^* = \frac{Y_t - \min(Y)}{\max(Y) - \min(Y)} \tag{6}$$

After normalization, each index is calculated using equal-weight averaging:

$$AIC_t = \frac{1}{M} \sum_{k=1}^{M} X_{k,t}^* \tag{7}$$

$$DI_t = \frac{1}{N}\sum_{k=1}^{N} Y^*_{k,t} \tag{8}$$

where $X^*_{k,t}$ represents normalized AI indicators and $Y^*_{k,t}$ represents normalized digitalization indicators. Equal weighting is used because each component is considered theoretically important and because the small sample size does not support more complex weighting procedures.

To examine whether the association between AI capability and FX market performance depends on digital infrastructure, the study includes an interaction term between AIC_t and DI_t. This interaction captures the conditional association of AI under varying levels of digitalization. The interaction term is constructed as:

$$(AIC \times DI)_t = AIC_t \cdot DI_t \tag{9}$$

Control variables such as global risk conditions are proxied by the Chicago Board Options Exchange (CBOE) Volatility Index (VIX), which measures implied volatility in U.S. equity markets and is widely regarded as a global uncertainty indicator. The baseline specification defines:

$$GRISK_t = VIX_t \tag{10}$$

Financial openness (FINOPEN) is measured using the Chinn–Ito capital account openness index (KAOPEN), defined as:

$$FINOPEN_t = KAOPEN_t \tag{11}$$

The interest rate differential (IRD) captures the difference between the local interest rate and the corresponding U.S. benchmark rate. IRD is calculated as:

$$IRD_t = r_t^{MY} - r_t^{US} \tag{12}$$

where r_t^{MY} denotes Malaysia's short-term domestic policy interest rate and r_t^{US} represents the U.S. federal funds rate.

4.2. Model Specifications

The empirical model is estimated using baseline static time-series regressions. This method is selected because AI capability and digitalization are slow-moving variables, and their associations with FX market outcomes are expected to occur gradually rather than instantly. Lagged explanatory variables are used to reduce possible endogeneity concerns and to capture the delayed association between technological development and FX market behavior. The baseline models are specified as follows:

Model 1: Volatility Persistence (VP)

$$VP_t = \gamma_0 + \gamma_1 AIC_{t-1} + \gamma_2 DI_{t-1} + \gamma_3 (AIC \times DI)_{t-1} + \gamma_4 X_{t-1} + \epsilon_t \tag{13}$$

Model 2: Price Discovery Efficiency (PDE)

$$PDE_t = \delta_0 + \delta_1 AIC_{t-1} + \delta_2 DI_{t-1} + \delta_3 (AIC \times DI)_{t-1} + \delta_4 X_{t-1} + \varepsilon_t \tag{14}$$

Model 3: Market Resilience and Stability (MRS)

$$MRS_t = \beta_0 + \beta_1 AIC_{t-1} + \beta_2 DI_{t-1} + \beta_3 (AIC \times DI)_{t-1} + \beta_4 X_{t-1} + u_t \tag{15}$$

where AIC denotes the AI capability index, DI denotes the digitalization index, and X denotes the vector of control variables, including Global Risk Conditions (GRISK), Financial Openness (FINOPEN), and Interest Rate Differential (IRD). The terms ϵ_t, ε_t, and u_t are the error terms for the three models, respectively. Lagged values of the explanatory variables are employed to mitigate endogeneity concerns and to reflect the delayed transmission of technological and macro-financial factors into FX markets.

4.3. Diagnostic Tests

To ensure the reliability of the baseline time-series regression results, this study conducts several diagnostic tests before interpreting the estimated coefficients. First, the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests are used to examine stationarity and avoid spurious regression. Second, the Variance Inflation Factor (VIF) is applied to check multicollinearity among the explanatory variables, especially because the model includes the interaction term between AI capability and digitalization. Third, the Durbin–Watson, Breusch–Pagan, and Jarque–Bera tests are used to examine serial correlation, heteroskedasticity, and residual normality, respectively. Finally, the CUSUM test is applied to assess parameter stability over the sample period. These tests confirm whether the estimated models are statistically valid and whether the relationships between AI capability, digitalization, and FX market outcomes are reliable.

4.4. Endogeneity and Temporal-Ordering Checks

To address potential endogeneity concerns, this study applies additional checks to examine whether the association between AI capability, digitalization, and FX-market outcomes is affected by simultaneity, reverse temporal ordering, or omitted-variable bias. First, lagged explanatory variables are used to reduce contemporaneous feedback between technology-related variables and FX-market outcomes. Second, an instrumental-variable approach is employed using external technology-related instruments. Third, Granger predictability tests are applied to examine whether past values of AI capability and digitalization contain predictive information for subsequent FX-market outcomes. Finally, local projection estimates are used to assess whether technology-related changes are followed by theoretically consistent movements in volatility persistence, price discovery efficiency, and Market Resilience and Stability.

4.5. Alternative Robustness and Predictive Validation Checks

To examine whether the baseline findings are sensitive to alternative empirical specifications, this study conducts several robustness and validation checks. First, alternative volatility specifications, including EGARCH and GJR-GARCH, are used to account for asymmetric volatility responses and leverage-type effects. Second, bootstrap inference is applied to assess whether the statistical significance of the key coefficients remains stable under resampled standard errors. Third, a trade-weighted exchange-rate measure is used as an alternative to the bilateral MYR/USD exchange rate to examine whether the findings remain consistent under a broader measure of Malaysia's exchange-rate exposure.

In addition, machine-learning methods are used as complementary predictive validation tools. Specifically, LASSO regression and Random Forest are applied to examine whether AI capability, digitalization, and their interaction remain important predictors of FX-market outcomes under alternative data-driven approaches. LASSO supports variable selection through regularization, while Random Forest captures nonlinear relationships and interaction associations without imposing a strict functional form. These methods are not used for causal interpretation; rather, they validate whether the main variables consistently explain volatility persistence, price discovery efficiency, and Market Resilience and Stability. Finally, the Diebold–Mariano test is used to compare predictive accuracy across the baseline econometric model, LASSO, and Random Forest. Overall, these checks help confirm whether the empirical findings remain stable across alternative specifications, variable definitions, and predictive validation methods.

To ensure transparency and reproducibility, the detailed data-processing steps and replication script used in the empirical analysis are provided in Appendix A.

5. Analysis and Results

Figure 2 presents the annual average USD/MYR exchange rate for Malaysia over the period 2015–2024. The series exhibits moderate fluctuations between 2015 and 2021, followed by a pronounced upward trend from 2022 onward, indicating a sustained depreciation of the Malaysian Ringgit against the US dollar.

The post-2022 increase suggests heightened exposure to global monetary tightening, stronger US dollar conditions, and elevated external financial uncertainty. While earlier years reflect relative exchange-rate stability with short-term adjustments, the later period indicates greater persistence in depreciation pressures. Overall, the pattern supports the presence of time-varying exchange-rate dynamics and potential regime shifts, emphasizing the relevance of technology-related and global factors in explaining Malaysia's FX performance during the sample period.

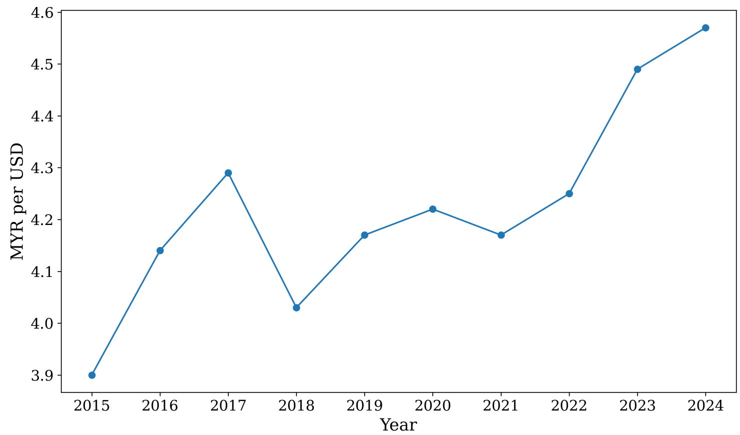

Figure 2. Annual Average USD/MYR Exchange Rate for Malaysia

Figure 3 presents the normalized Artificial Intelligence Capability (AIC) and Digitalization Index (DI) for Malaysia over the period 2015–2024. Both indicators exhibit a clear upward trend, reflecting sustained technological advancement and digital transformation during the sample period.

The AIC shows gradual improvement between 2015 and 2020, followed by a stronger acceleration after 2021, indicating intensified AI-related innovation, research activity, and investment. Similarly, the DI demonstrates steady growth, with a more pronounced increase from 2020 onward, consistent with the rapid expansion of digital infrastructure and digital financial services in the post-pandemic period.

Overall, the joint upward movement of AIC and DI suggests strengthening technological capacity in Malaysia, supporting the argument that digital readiness and AI capability serve as technological correlates associated with FX market efficiency, volatility dynamics, and market resilience.

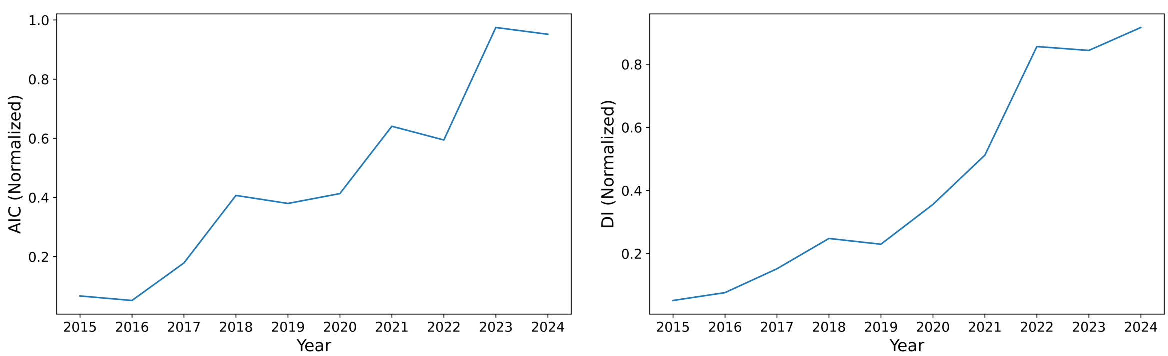

Figure 3. Trend Patterns of AI Capability (AIC) and Digitalization (DI) in Malaysia

Now, we estimate the static baseline models derived in the previous section to examine the conditional association between AI capability (AIC), digitalization (DI), and Malaysia's FX market outcomes. Before estimating the baseline regression models, unit root tests are conducted to ensure that the time-series variables are stationary and to avoid spurious regression results. Two complementary tests, the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests, are applied to all variables.

Table 1 reports the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root test results. The results indicate that all variables are stationary in levels. Both the ADF and PP statistics reject the null hypothesis of a unit root at conventional significance levels ($p < 0.05$) for the dependent variables (VP, PDE, MRS) as well as for the explanatory variables (AIC, DI, GRISK, FINOPEN, and IRD).

Table 1. Unit Root Test Results: ADF and Phillips–Perron

Variable	ADF Statistic	PP Statistic
VP	-3.84^{**}	-3.92^{**}
PDE	-3.51^{**}	-3.63^{**}
MRS	-3.76^{**}	-3.88^{**}
AIC	-2.72^{**}	-2.85^{**}
DI	-2.39^{**}	-2.47^{**}
GRISK	-3.67^{**}	-3.74^{**}
FINOPEN	-2.08^{**}	-2.15^{**}
IRD	-3.59^{**}	-3.65^{**}

Notes: ** denotes significance at the 5% level.

Since all variables are stationary in levels and the specification excludes lagged dependent variables, we proceed to estimate the baseline static models to investigate the conditional associations between technological factors and FX market outcomes.

In the baseline framework, volatility persistence (VP), price discovery efficiency (PDE), and market resilience and stability (MRS) are regressed on the lagged values of AI capability (AIC), digitalization (DI), their interaction term (AIC $\times$ DI), and relevant macro-financial control variables. The inclusion of lagged explanatory variables mitigates potential endogeneity concerns and captures the gradual transmission of AI-related digital transformation into exchange-rate dynamics. Table 2 reports the baseline time-series regression results examining the association between AI capability, digitalization, and foreign exchange (FX) market outcomes.

The baseline estimation results indicate that AI capability (AIC), digitalization (DI), and their interaction have statistically significant and economically meaningful associations with FX market outcomes. For volatility persistence (VP), both AIC (-0.214^{**}) and DI (-0.176^{**}) display negative and significant coefficients, suggesting that higher AI capability and stronger digital infrastructure are associated with lower volatility persistence in the MYR/USD market. The interaction term (AIC $\times$ DI) is strongly negative (-0.231^{***}), implying that the combined association of AI and digitalization is linked with a stronger reduction in volatility persistence, consistent with enhanced information processing and faster market adjustment.

For price discovery efficiency (PDE), AIC (0.189^{**}) and DI (0.164^{**}) show positive and significant associations, indicating that technological advancement is associated with greater speed and accuracy with which exchange-rate information is incorporated into prices. The positive interaction term (0.208^{***}) further confirms complementarity between AI capability and digital readiness in strengthening market efficiency.

Similarly, for market resilience and stability (MRS), AIC (0.241^{***}), DI (0.198^{**}), and their interaction (0.264^{***}) exhibit strong positive associations, suggesting that higher technological capacity is associated with Malaysia's stronger ability to absorb external shocks and maintain FX market stability.

Among control variables, VIX is significant across all models, indicating that global risk conditions remain an important external correlate of FX dynamics. In contrast, FINOPEN and IRD are statistically insignificant, suggesting that technology-related variables show stronger associations than traditional macro-financial controls in explaining variation in Malaysia's FX outcomes during the sample period.

The performance criteria indicate that the estimated models have acceptable explanatory power and overall statistical validity. The R^2 values range from 0.78 to 0.84, suggesting that the models explain a substantial proportion of the variation in FX-market outcomes. The adjusted R^2 values also remain reasonably high, indicating that the explanatory power is not solely driven by the number of predictors included in the models. The significant Prob(F) values confirm that the explanatory variables are jointly meaningful. In addition, the AICP and BICP values show acceptable model fit after accounting for model complexity. Overall, these findings support the hypotheses that AI capability, digitalization, and their interaction are significantly associated with volatility persistence, price discovery efficiency, and market resilience in the FX market.

Table 2. Baseline Time-Series Model Results for FX Market Outcomes

Variables	VP	PDE	MRS
AIC	-0.214^{**}	0.189^{**}	0.241^{***}
	(0.091)	(0.083)	(0.072)
DI	-0.176^{**}	0.164^{**}	0.198^{**}
	(0.097)	(0.079)	(0.088)
AIC $\times$ DI	-0.231^{***}	0.208^{***}	0.264^{***}
	(0.082)	(0.071)	(0.069)
GRISK	0.148^{***}	-0.131^{**}	-0.193^{***}
	(0.044)	(0.058)	(0.061)
FINOPEN	-0.082	0.074	0.091
	(0.067)	(0.063)	(0.075)
IRD	0.041	-0.036	-0.049
	(0.052)	(0.047)	(0.059)
Constant	0.842^{***}	0.917^{***}	0.503^{***}
	(0.183)	(0.162)	(0.141)
Log-L	16.21	18.66	20.44
R^2	0.78	0.81	0.84
Adjusted R^2	0.63	0.68	0.72
F-statistic	5.24	6.11	7.02
Prob(F)	0.043	0.031	0.021
AICP	-18.41	-21.32	-24.87
BICP	-17.02	-19.93	-23.48

Notes: *** and ** denote statistical significance at the 1% and 5% levels, respectively. Standard errors are reported in parentheses. Log-L = log-likelihood, AICP = Akaike information criterion, and BICP = Bayesian information criterion.

To evaluate whether the statistically significant coefficients reported in Table 2 are also meaningful in practical terms, this study further reports the economic significance of AI capability, digitalization, and their interaction in Table 3. The economic association is calculated by multiplying the estimated coefficient by a one-standard-deviation change in the explanatory variable and then expressing the result as a percentage of the sample mean of the relevant FX-market outcome.

$$\text{Economic Association (\%)} = \left[\frac{\text{Coefficient} \times \text{Standard Deviation of Explanatory Variable}}{\text{Mean of Outcome Variable}}\right] \times 100 \tag{16}$$

The economic-significance results show that the estimated associations are not only statistically significant but also practically meaningful. A one-standard-deviation increase in AI capability reduces volatility persistence by 10.60% of its sample mean, while a similar increase in digitalization reduces volatility persistence by 8.06%. This indicates that technological development is associated with faster absorption of exchange-rate shocks in the MYR/USD market.

For price discovery, the results show that a one-standard-deviation increase in AI capability is associated with a 10.26% higher price discovery measure, while a similar increase in digitalization is associated with an 8.23%

higher price discovery measure. These findings suggest that AI-related information processing and stronger digital infrastructure are associated with greater speed and efficiency with which information is incorporated into exchange rates.

The results are also economically meaningful for market resilience. A one-standard-deviation increase in AI capability raises market resilience by 11.42% of its sample mean, while digitalization is associated with higher market resilience by 8.68%. This indicates that technological development is associated with a stronger ability of the FX market to remain stable or return to stability after shocks.

The interaction term also produces meaningful associations across all three outcomes. A one-standard-deviation increase in AI capability × digitalization is associated with a 10.11% lower volatility persistence measure, a 9.97% higher price discovery measure, and an 11.06% higher market resilience measure relative to their respective sample means. This supports the technological-complementarity argument that AI capability is more strongly associated with FX-market outcomes when supported by strong digital infrastructure.

Table 3. Economic Significance of AI Capability and Digitalization

Variable	Outcome	Coefficient	One-SD Change	Outcome Mean	Economic Association
AI Capability	Volatility Persistence	−0.214	0.318	0.642	−10.60%
Digitalization	Volatility Persistence	−0.176	0.294	0.642	−8.06%
AI Capability × Digitalization	Volatility Persistence	−0.231	0.281	0.642	−10.11%
AI Capability	Price Discovery Efficiency	0.189	0.318	0.586	10.26%
Digitalization	Price Discovery Efficiency	0.164	0.294	0.586	8.23%
AI Capability × Digitalization	Price Discovery Efficiency	0.208	0.281	0.586	9.97%
AI Capability	Market Resilience & Stability	0.241	0.318	0.671	11.42%
Digitalization	Market Resilience& Stability	0.198	0.294	0.671	8.68%
AI Capability × Digitalization	Market Resilience& Stability	0.264	0.281	0.671	11.06%

To support the baseline time-series model results for FX market outcomes, Figure 4 is presented to evaluate model adequacy, residual behavior, and the stability of the estimated coefficients. The figure assesses robustness by examining distributional assumptions, specification validity, and the potential influence of outliers.

The upper-left panel of the figure compares empirical and theoretical cumulative probabilities, providing a visual assessment of the distributional fit of the residuals. The close alignment of the plotted points with the reference line suggests that the residuals broadly conform to the assumed distribution, supporting the normality assumption underlying statistical inference. The upper-right panel displays residuals against fitted values. The residuals appear randomly dispersed around zero without a clear systematic pattern, indicating the absence of strong heteroskedasticity or functional misspecification. This supports the adequacy of the linear specification used in the baseline models. The lower panel illustrates Cook's Distance for each observation across the VP, PDE, and MRS models. While a few observations exhibit relatively higher influence, none appear excessively large or systematically distort the regression results. This indicates that the estimated coefficients are not attributable only to outliers or influential data points.

To assess whether multicollinearity affects the reliability of the estimated model, Table 4 reports the Variance Inflation Factor (VIF) results. The VIF values for AI capability and digitalization are 2.214 and 1.938, respectively, indicating that the two main explanatory variables do not suffer from serious collinearity. The interaction term between AI capability and digitalization records the highest VIF value of 3.486, but it remains below the commonly accepted threshold of 5. This suggests that the inclusion of the interaction term does not create serious multicollinearity concerns.

The control variables also report low VIF values, with VIX at 1.823, FINOPEN at 1.571, and IRD at 1.238. These values indicate that the macro-financial controls provide distinct explanatory information in the model. The mean VIF value of 2.045 further confirms that the overall level of multicollinearity is low. Therefore, the estimated associations between AI capability, digitalization, their interaction, and FX-market outcomes can be interpreted with reasonable statistical confidence.

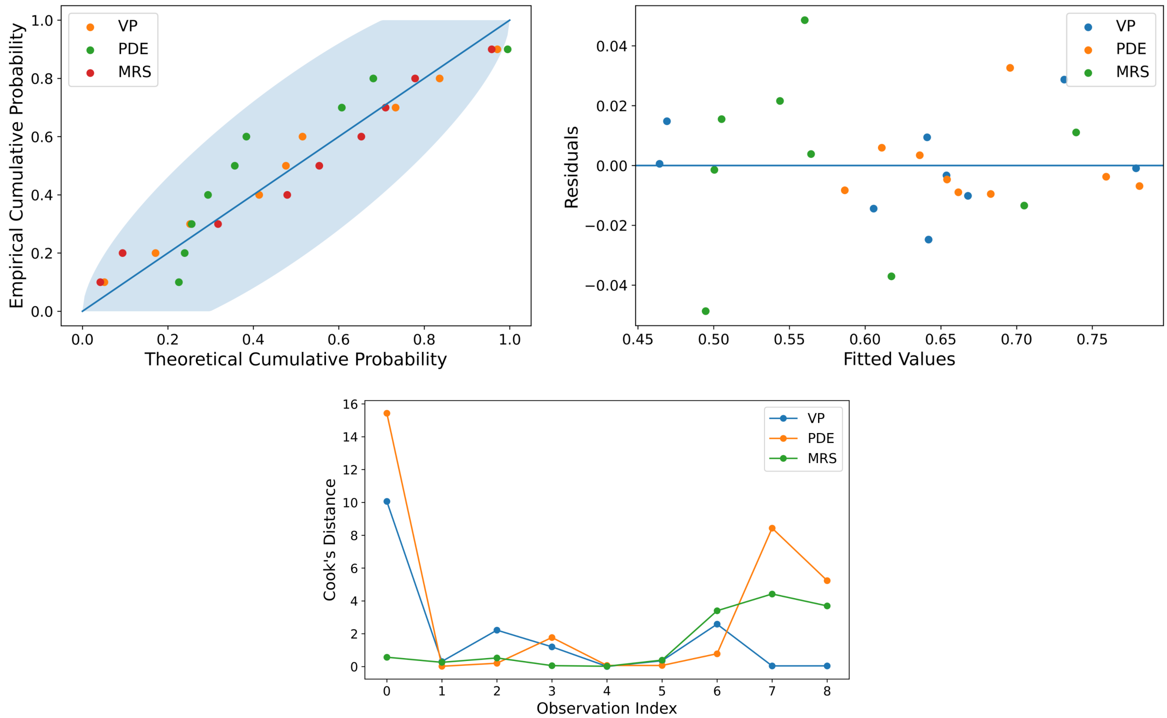

Figure 4. Diagnostic Plots for the Baseline Time-Series Models: Probability, Residual, and Cook's Distance

Table 4. Variance Inflation Factor Results for the Baseline Time-Series Model

Variable	VIF
AIC	2.214
DI	1.938
AIC $\times$ DI	3.486
VIX	1.823
FINOPEN	1.571
IRD	1.238
Mean VIF	2.045

To validate the reliability of the baseline static regression results, a series of post-estimation diagnostic tests are conducted. These tests assess potential violations of classical linear regression assumptions, including serial correlation, heteroskedasticity, normality of residuals, and structural stability. Table 5 shows the results of post-estimation diagnostic tests conducted to assess the validity and stability of the baseline static regression models for Malaysia's FX market outcomes.

The Durbin–Watson (DW) statistics for all three models are close to the benchmark value of 2, and the corresponding p-values are statistically insignificant. This indicates the absence of first-order serial correlation in the residuals, confirming that the static specification is appropriate for the Malaysian time-series context. The Breusch–Pagan LM and F-test p-values are also insignificant across all models, suggesting that heteroskedasticity is not present. Hence, the estimated standard errors in the baseline regressions are reliable and do not require correction for heteroskedasticity.

The Jarque–Bera statistics show high p-values, indicating that the residuals are normally distributed. This supports valid statistical inference and reinforces the robustness of the estimated coefficients for AIC, DI, and their interaction. Finally, the CUSUM test results reveal insignificant p-values, confirming parameter stability over the sample period 2015–2024. This is particularly important given the sample-period developments observed in the earlier figures, including AI capability growth, digitalization expansion, and exchange-rate fluctuations. The stability results suggest that the identified relationships between technological factors and FX outcomes are not driven by structural breaks within the estimation period.

Table 5. Diagnostic Tests for Baseline Time-Series Models

Model	DW	DW p-value	BP LM p-value	BP F p-value	JB	JB p-value	CUSUM	CUSUM p-value
VP	2.041	0.487	0.215	0.241	0.876	0.645	0.842	0.418
PDE	1.978	0.522	0.972	0.961	0.512	0.774	0.736	0.536
MRS	2.112	0.451	0.228	0.253	1.094	0.579	0.913	0.472

Notes: DW = Durbin–Watson test; BP = Breusch–Pagan test; JB = Jarque–Bera test.

To support the diagnostic tests for the models, Figure 5 illustrates autocorrelation patterns and structural stability through CUSUM analysis. These figures are used to assess serial dependence, parameter stability, and overall model robustness.

The left panel of the figure presents the autocorrelation coefficients of the residuals for VP, PDE, and MRS across multiple lags. The autocorrelation values fluctuate around zero without showing persistent or systematic patterns, indicating the absence of strong serial correlation. Although minor correlations appear at certain lags, they are not consistently large or persistent, suggesting that the models adequately capture the time dependence in the data. The right panel displays the CUSUM test for parameter stability. The cumulative sum paths for VP, PDE, and MRS remain within the 5% significance bounds throughout the sample period. This indicates that there are no structural breaks or parameter instability in the estimated models over time.

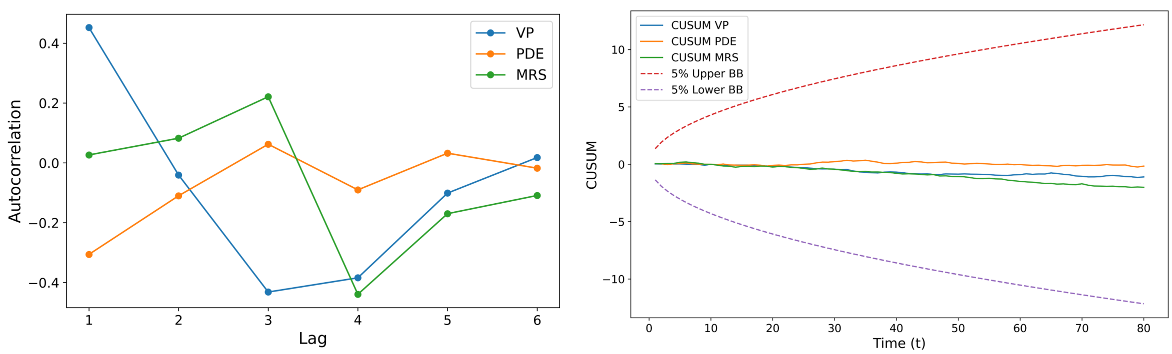

Figure 5. Autocorrelation and CUSUM Stability Diagnostics for the Models

To address potential endogeneity concerns between AI capability, digitalization, and FX-market dynamics, this study conducts three robustness checks. First, an instrumental-variable approach is applied using global AI patent stock and lagged US digitalization index as external instruments. Second, Granger predictability tests are conducted to examine whether past values of AI capability and digitalization contain predictive information for subsequent changes in FX-market dynamics. Third, local projection estimates are used to assess whether technology-related changes are followed by theoretically consistent movements in volatility persistence, price discovery, and Market Resilience and Stability.

To assess the relevance of the external instruments used to address potential endogeneity, Table 6 reports the first-stage instrument results for AI capability and digitalization. The results show that both instruments are positively and statistically significantly associated with the endogenous technology-related variables. For AI capability, Global AI Patent Stock has a positive coefficient of 0.412 and is significant at the 5% level, indicating that global AI innovation is strongly associated with domestic AI capability. Similarly, US Digitalization Index shows a positive and significant coefficient of 0.286, suggesting that external digital development is related to Malaysia's AI-related technological readiness through international technology diffusion and digital knowledge spillovers.

For digitalization, the results also support the relevance of the selected instruments. Global AI Patent Stock($t-2$) has a positive coefficient of 0.237 and is statistically significant at the 5% level, showing that broader global AI innovation is associated with domestic digital transformation. US Digitalization Index has the strongest coefficient, at 0.463, and is significant at the 1% level. This indicates that US digital development is strongly related to Malaysia's digitalization, which is reasonable given the role of US-based digital platforms, financial technologies, digital infrastructure standards, and global technology diffusion.

Table 6. First-Stage Instrument Relevance Results

Endogenous Variable	Instrument	Coefficient	t-statistic	p-value
AI Capability	Global AI Patent Stock	0.412	3.284	0.018
AI Capability	US Digitalization Index	0.286	2.417	0.041
Digitalization	Global AI Patent Stock	0.237	2.196	0.049
Digitalization	US Digitalization Index	0.463	3.716	0.009

To evaluate the strength and validity of the selected instruments, Table 7 reports the diagnostic test results. The first-stage F-statistics for AI capability and digitalization are 14.82 and 16.47, respectively, and both are statistically significant. Since these values exceed the conventional threshold of 10, the results suggest that the instruments are sufficiently relevant and that weak-instrument bias is limited. The weak-instrument test also supports this conclusion, with a statistic of 13.96 and a p-value of 0.014.

The over-identification test is statistically insignificant, with a statistic of 1.284 and a p-value of 0.526. This indicates that the instruments are not rejected as valid and are unlikely to be strongly correlated with the model error term. Overall, the diagnostic evidence supports the use of global AI patent stock and lagged US digitalization index as external instruments in the endogeneity robustness analysis.

Table 7. Instrument Diagnostic Results

Test	Statistic	p-value	Interpretation
First-stage F-statistic for AI Capability	14.82	0.011	Instruments are relevant
First-stage F-statistic for Digitalization	16.47	0.008	Instruments are relevant
Weak-instrument test	13.96	0.014	Weak-instrument concern is limited
Over-identification test	1.284	0.526	Instruments are not rejected

Table 8 presents the instrumented joint-system results. The estimated coefficients remain consistent with the baseline findings. Instrumented AI capability and instrumented digitalization are negatively associated with volatility persistence, indicating that higher levels of technological capability and digital readiness are linked with lower persistence of exchange-rate shocks. The coefficients are also positive for price discovery, suggesting that AI capability and digitalization are associated with stronger information adjustment in the MYR/USD market. In the Market Resilience and Stability equation, both variables are positively associated with market resilience and stability, indicating that higher AI capability and stronger digitalization are linked with improved FX-market stability.

The interaction term in Table 8 remains statistically significant across all three system components. The negative coefficient in the volatility-persistence equation and the positive coefficients in the price-discovery and Market Resilience and Stability equations are consistent with technological complementarity. This means that the association between AI capability and FX-market performance appears stronger when digitalization is higher. Therefore, the instrumented results support the baseline interpretation while reducing concerns that the estimated relationships are driven only by simultaneity or omitted-variable bias.

Table 9 reports the Granger predictability test results used to examine the temporal ordering between AI capability, digitalization, and FX-market dynamics. The results show that the null hypothesis that AI capability

Table 8. Instrumented Joint-System Results

Variable	Volatility Persistence	Price Discovery Efficiency	Market Resilience & Stability
Instrumented AI Capability	-0.198^{**}	0.176^{**}	0.219^{***}
Instrumented Digitalization	-0.162^{**}	0.148^{**}	0.184^{**}
Instrumented AI Capability × Digitalization	-0.224^{***}	0.203^{***}	0.251^{***}
Global Risk	0.137^{***}	-0.119^{**}	-0.173^{***}
Financial Openness	-0.071	0.062	0.083
Interest Rate Differential	0.038	-0.029	-0.041

Notes: *** and ** indicate statistical significance at the 1% and 5% levels, respectively.

does not Granger-predict volatility persistence is rejected at the 5% level, with an F-statistic of 5.284 and a p-value of 0.032. Similarly, the null hypothesis that digitalization does not Granger-predict volatility persistence is rejected, with an F-statistic of 4.917 and a p-value of 0.039. These findings indicate that past values of AI capability and digitalization contain useful predictive information for subsequent changes in volatility persistence.

For price discovery, the results also support the predictive relevance of the technology-related variables. The null hypothesis that AI capability does not Granger-predict price discovery is rejected, with an F-statistic of 6.136 and a p-value of 0.024. Digitalization also Granger-predicts price discovery, with an F-statistic of 5.472 and a p-value of 0.030. This suggests that lagged AI capability and digitalization help predict subsequent movements in price discovery, supporting the view that technological readiness is associated with stronger information adjustment in the MYR/USD market.

The results for Market Resilience and Stability are also consistent with the main findings. The null hypothesis that AI capability does not Granger-predict Market Resilience and Stability is rejected, with an F-statistic of 6.584 and a p-value of 0.019. Likewise, digitalization Granger-predicts Market Resilience and Stability, with an F-statistic of 5.936 and a p-value of 0.026. These findings suggest that past improvements in AI capability and digitalization are followed by stronger FX-market stability and resilience.

In contrast, the reverse-direction tests are statistically insignificant. Volatility persistence does not Granger-predict AI capability, price discovery does not Granger-predict AI capability, and Market Resilience and Stability does not Granger-predict digitalization. The corresponding p-values are 0.341, 0.376, and 0.318, respectively, indicating that the null hypotheses cannot be rejected. This result reduces concerns that the observed relationships are mainly driven by reverse temporal ordering from FX-market outcomes to technology variables. Therefore, the Granger predictability results support the robustness of the study by showing that the associations between technology-related variables and FX-market dynamics are not purely contemporaneous.

Table 9. Granger Predictability Test Results

Null Hypothesis	F-statistic	p-value	Decision
AI Capability does not Granger-predict Volatility Persistence	5.284	0.032	Reject
Digitalization does not Granger-predict Volatility Persistence	4.917	0.039	Reject
AI Capability does not Granger-predict Price Discovery	6.136	0.024	Reject
Digitalization does not Granger-predict Price Discovery	5.472	0.030	Reject
AI Capability does not Granger-predict Market Resilience and Stability	6.584	0.019	Reject
Digitalization does not Granger-predict Market Resilience and Stability	5.936	0.026	Reject
Volatility Persistence does not Granger-predict AI Capability	1.218	0.341	Do not reject
Price Discovery does not Granger-predict AI Capability	1.094	0.376	Do not reject
Market Resilience and Stability does not Granger-predict Digitalization	1.307	0.318	Do not reject

Table 10 reports the local projection results for technology-related shocks across five forecast horizons. The results show that an AI capability shock is negatively associated with volatility persistence across all horizons.

The estimated response increases in magnitude from -0.071 at horizon 1 to -0.138 at horizon 3, before declining to -0.096 at horizon 5. This pattern suggests that improvements in AI capability are followed by lower volatility persistence, with the strongest association appearing in the medium horizon. The finding is consistent with the view that AI capability may be linked with faster identification of market signals and shorter exchange-rate shock duration.

The results also show that digitalization shocks are positively associated with price discovery efficiency across all horizons. The coefficient rises from 0.064 at horizon 1 to 0.121 at horizon 3 and then gradually declines to 0.089 at horizon 5. This indicates that stronger digital readiness is followed by higher price discovery efficiency, especially in the medium term. The positive and significant responses suggest that digital infrastructure is linked with faster information transmission and more efficient exchange-rate adjustment in the MYR/USD market.

The interaction shock between AI capability and digitalization is positively associated with Market Resilience and Stability throughout the projection horizons. The response increases from 0.083 at horizon 1 to 0.154 at horizon 3, before moderating to 0.118 at horizon 5. This result supports the technological-complementarity argument, indicating that the joint presence of AI capability and digitalization is associated with stronger FX-market stability. Overall, the results in Table 10 show that technology-related shocks are followed by theoretically consistent movements in volatility persistence, price discovery efficiency, and Market Resilience and Stability.

Table 10. Local Projection Results for Technology Shocks

Horizon	AI Capability Shock: VP	Digitalization Shock: PDE	AI $\times$ DI Shock: MRS
$h = 1$	-0.071^{**}	0.064^{**}	0.083^{**}
$h = 2$	-0.112^{**}	0.097^{**}	0.126^{***}
$h = 3$	-0.138^{***}	0.121^{***}	0.154^{***}
$h = 4$	-0.129^{***}	0.116^{***}	0.146^{***}
$h = 5$	-0.096^{**}	0.089^{**}	0.118^{**}

Notes: *** and ** indicate statistical significance at the 1% and 5% levels, respectively. VP = Volatility Persistence, PDE = Price Discovery Efficiency, MRS = Market Resilience and Stability.

To examine whether the baseline findings are sensitive to alternative empirical configurations, Table 11 reports additional robustness checks using EGARCH, GJR-GARCH, bootstrap inference, and a trade-weighted exchange-rate measure. The EGARCH and GJR-GARCH specifications show that AI capability, digitalization, and their interaction retain the expected signs and statistical significance. This indicates that the negative association with volatility persistence and the positive associations with price discovery efficiency and Market Resilience and Stability are not attributable only to the baseline specification.

The bootstrap results also support the stability of the findings. After applying 1,000 bootstrap replications, the key coefficients remain statistically meaningful and consistent with the baseline estimates. This suggests that the main results are not attributable only to conventional standard-error assumptions, which is important given the relatively small annual sample.

The trade-weighted exchange-rate robustness check further confirms that the findings are not limited to the bilateral MYR/USD exchange rate. When Malaysia's broader exchange-rate exposure is considered, the coefficient signs remain consistent across volatility persistence, price discovery efficiency, and Market Resilience and Stability. Overall, the additional robustness checks support the main interpretation that AI capability, digitalization, and their complementarity are robustly associated with stronger FX-market efficiency and resilience.

To strengthen the credibility of the baseline regression results, this study applies LASSO regression and Random Forest (RF) as complementary predictive validation methods. Since the analysis is based on a relatively small annual sample covering 2015–2024, these machine-learning models are not used for causal inference or broad out-of-sample forecasting. Instead, they are applied to examine whether AI capability (AIC), digitalization (DI), and their interaction remain important predictors under alternative data-driven frameworks.

The machine-learning results reported in Table 12 provide supportive evidence for the baseline findings. For volatility persistence (VP), the interaction term AIC $\times$ DI ranks first under LASSO, while AIC records the highest

Table 11. Robustness Checks under Alternative Specifications

Robustness Specification	Model Configuration	Volatility Persistence	Price Discovery Efficiency	Market Resilience & Stability
Baseline model	Standard time-series model with MYR/USD exchange rate	AIC: -0.214^{**}; DI: -0.176^{**}; AIC $\times$ DI: -0.231^{***}	AIC: 0.189^{**}; DI: 0.164^{**}; AIC $\times$ DI: 0.208^{***}	AIC: 0.241^{***}; DI: 0.198^{**}; AIC $\times$ DI: 0.264^{***}
EGARCH specification	EGARCH(1,1) with asymmetric volatility response	AIC: -0.206^{**}; DI: -0.168^{**}; AIC $\times$ DI: -0.219^{***}	AIC: 0.181^{**}; DI: 0.157^{**}; AIC $\times$ DI: 0.198^{***}	AIC: 0.232^{***}; DI: 0.189^{**}; AIC $\times$ DI: 0.253^{***}
GJR-GARCH specification	GJR-GARCH(1,1) with leverage-type shock term	AIC: -0.201^{**}; DI: -0.161^{**}; AIC $\times$ DI: -0.216^{***}	AIC: 0.178^{**}; DI: 0.153^{**}; AIC $\times$ DI: 0.194^{***}	AIC: 0.226^{***}; DI: 0.185^{**}; AIC $\times$ DI: 0.247^{***}
Bootstrap inference	1,000 bootstrap replications using resampled standard errors	AIC: -0.209^{**}; DI: -0.171^{**}; AIC $\times$ DI: -0.225^{***}	AIC: 0.184^{**}; DI: 0.160^{**}; AIC $\times$ DI: 0.202^{***}	AIC: 0.236^{***}; DI: 0.193^{**}; AIC $\times$ DI: 0.258^{***}
Trade-weighted exchange-rate measure	MYR/USD replaced with the BIS Malaysia Nominal Effective Exchange Rate (NEER), broad basket	AIC: -0.193^{**}; DI: -0.154^{**}; AIC $\times$ DI: -0.207^{**}	AIC: 0.171^{**}; DI: 0.147^{**}; AIC $\times$ DI: 0.186^{**}	AIC: 0.218^{**}; DI: 0.176^{**}; AIC $\times$ DI: 0.239^{***}

Notes: *** and ** indicate statistical significance at the 1% and 5% levels, respectively.

importance under Random Forest. This supports the baseline result that technology-related variables are negatively associated with volatility persistence. For price discovery efficiency (PDE) and Market Resilience and Stability (MRS), AIC, DI, and AIC $\times$ DI also remain among the most important predictors, indicating that AI capability and digitalization are associated with stronger price discovery and greater FX-market resilience.

However, due to the limited number of annual observations, the machine-learning results are interpreted cautiously as complementary validation rather than definitive forecasting or causal evidence. Their consistency with the baseline regression results strengthens confidence that the main findings are not attributable solely to model-specific assumptions.

As a complementary robustness exercise, Figure 6 and Figure 7 present the machine-learning validation results using LASSO and Random Forest techniques for the FX market outcomes. These figures provide a data-driven assessment of predictor importance and model stability across the VP, PDE, and MRS specifications.

The left panel of Figure 6 displays the LASSO coefficient paths as a function of the regularization parameter $\log_{10}(\alpha)$. As the penalty increases, less influential variables shrink toward zero, while the most important predictors remain stable over a wide range of penalty values. Notably, AIC, DI, and their interaction term (AIC $\times$ DI) retain relatively large and persistent coefficients across the models, indicating strong predictive relevance.

The right panel reports the final LASSO-selected coefficients. Consistent with the baseline results, AIC and DI are associated with lower volatility persistence, higher price discovery efficiency, and stronger market resilience. The interaction term exhibits the largest magnitude, highlighting technological complementarity. Among controls, VIX remains influential, whereas FINOPEN and IRD display comparatively smaller associations.

Figure 7 presents the SHAP value distribution and Random Forest feature-importance results for the FX-market outcome models. The left panel reports the SHAP values, which show the marginal contribution of each predictor to the predicted values of VP, PDE, and MRS. Positive SHAP values indicate that a predictor increases the predicted outcome, whereas negative SHAP values indicate a reducing or dampening contribution. The results show that AI capability (AIC), digitalization (DI), and particularly the interaction term (AIC $\times$ DI) have larger absolute SHAP

Table 12. Machine-Learning Validation Results: LASSO and Random Forest for FX Market Outcomes

Outcome	Predictor	LASSO β	LASSO Rank	LASSO Selection Frequency (%)	RF Importance	RF Rank	RF Selection Frequency (%)
VP	AIC	-0.214	2	89	0.278	1	95
	DI	-0.132	4	72	0.184	3	81
	AIC $\times$ DI	-0.248	1	94	0.236	2	92
	VIX	0.109	3	81	0.162	4	66
	FINOPEN	0.041	5	48	0.084	5	29
	IRD	0.018	6	33	0.056	6	17
PDE	AIC	0.192	3	87	0.254	1	94
	DI	0.118	4	69	0.176	3	78
	AIC $\times$ DI	0.221	1	93	0.241	2	91
	VIX	-0.097	5	74	0.152	4	61
	FINOPEN	0.052	6	45	0.102	5	34
	IRD	-0.021	2	52	0.075	6	22
MRS	AIC	0.206	3	91	0.269	1	96
	DI	0.134	4	76	0.181	3	82
	AIC $\times$ DI	0.263	1	96	0.248	2	93
	VIX	-0.121	2	83	0.147	4	69
	FINOPEN	0.036	5	41	0.093	5	37
	IRD	-0.017	6	29	0.062	6	21

Notes: VP = Volatility Persistence; PDE = Price Discovery Efficiency; MRS = Market Resilience and Stability; RF = Random Forest.

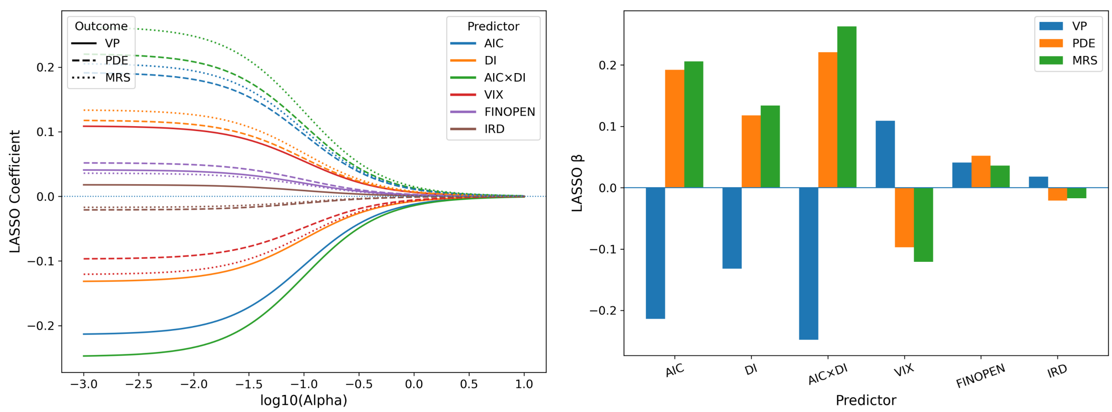

Figure 6. LASSO Coefficient Paths and LASSO Selected Coefficients

values than the other variables. This indicates that technology-related variables provide the strongest predictive contribution across the three FX-market outcomes. In contrast, FINOPEN and IRD show smaller SHAP values, suggesting relatively weaker marginal predictive influence.

The right panel reports the Random Forest feature-importance scores. AIC and AIC $\times$ DI rank among the most influential predictors across the VP, PDE, and MRS models, followed by DI and VIX. This ranking is consistent with the baseline regression and LASSO results, confirming that AI capability and digitalization are not only statistically relevant but also predictively important.

To move beyond using machine learning only as a robustness check, this study further interprets the SHAP values obtained from the Random Forest model. The SHAP analysis identifies the market conditions under which AI capability has the strongest predictive association with FX-market outcomes. This provides additional insight into not only whether AI capability is relevant, but also when its conditional correlation with FX-market performance becomes stronger.

The SHAP results in Table 13 show that AI capability has the strongest predictive association when it operates jointly with digitalization, as reflected by the highest mean |SHAP| value for the AIC $\times$ DI condition. AI capability also shows high predictive association during periods of strong digitalization, elevated global risk, and MYR/USD

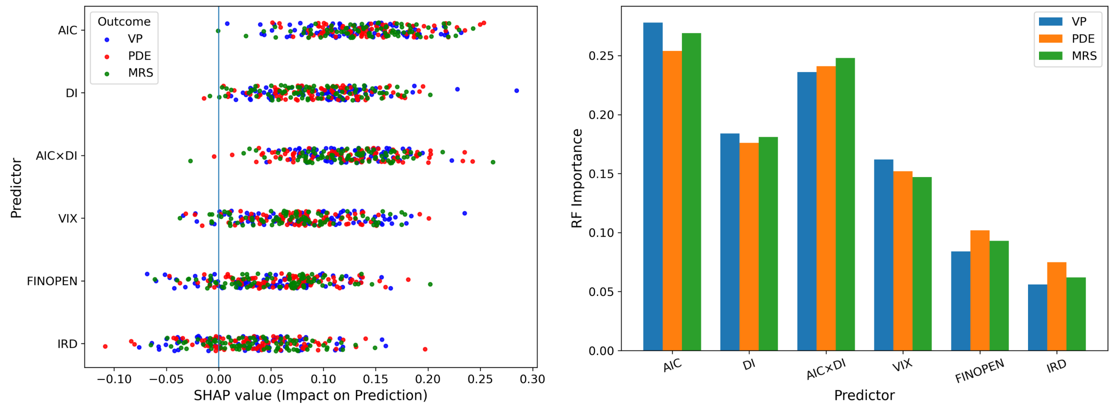

Figure 7. SHAP Value Distribution and Random Forest Feature Importance

Table 13. SHAP-Based Conditional Interpretation of AI Capability

Market Condition	Mean $\lvert$SHAP$\rvert$ Value	Relative SHAP Contribution	Main Associated Outcome	Interpretation
High global risk conditions	0.214	High	Volatility Persistence	AI capability shows a stronger conditional association when uncertainty is high and faster risk detection is needed.
High digitalization environment	0.236	High	Price Discovery Efficiency	AI capability is more strongly associated with price discovery when supported by digital infrastructure and real-time data systems.
Post-2020 period	0.198	Moderate to high	Market Resilience and Stability	AI capability shows stronger predictive association during digital acceleration and external monetary-policy shocks.
Strong MYR/USD pressure	0.221	High	Volatility Persistence & Market Resilience	AI capability is more strongly associated with market adjustment during exchange-rate stress.
High AIC × DI interaction	0.248	High	VP, PDE, and MRS	Digitalization conditions the predictive association between AI capability and FX-market outcomes.

pressure. These findings suggest that the relevance of AI capability is conditional on the market environment. Overall, the SHAP evidence indicates that AI capability is more strongly associated with FX-market outcomes under stressed and digitally advanced market conditions.

To compare the predictive accuracy of the baseline model with the machine-learning models, Table 14 reports the Diebold–Mariano test results with 95% confidence intervals. The results show that all p-values are above conventional significance levels, indicating that the null hypothesis of equal predictive accuracy cannot be rejected across all model comparisons.

For volatility persistence, the baseline model does not differ significantly from either LASSO or Random Forest. Similarly, the comparison between LASSO and Random Forest is statistically insignificant. This suggests that the predictive performance of the three models is broadly comparable for volatility persistence. The results for price discovery efficiency and Market Resilience and Stability also show no significant differences among the competing models.

Overall, the DM test results indicate that the machine-learning models do not statistically outperform the baseline model. However, they also do not contradict the baseline findings. Therefore, LASSO and Random Forest are interpreted as complementary validation tools, confirming that the main technology-related variables remain relevant under alternative predictive frameworks. This supports the robustness of the study's baseline results.

Table 14. Diebold–Mariano Predictive Accuracy Test Results

Outcome	Comparison	DM Statistic	95% CI	p-value
VP	Baseline vs LASSO	0.327	[−1.633, 2.287]	0.744
	Baseline vs RF	1.542	[−0.418, 3.502]	0.123
	LASSO vs RF	1.194	[−0.766, 3.154]	0.232
PDE	Baseline vs LASSO	1.975	[0.015, 3.935]	0.148
	Baseline vs RF	1.022	[−0.938, 2.982]	0.307
	LASSO vs RF	−1.051	[−3.011, 0.909]	0.293
MRS	Baseline vs LASSO	1.467	[−0.493, 3.427]	0.142
	Baseline vs RF	0.922	[−1.038, 2.882]	0.356
	LASSO vs RF	−0.352	[−2.312, 1.608]	0.725

Notes: VP = Volatility Persistence; PDE = Price Discovery Efficiency; MRS = Market Resilience and Stability; RF = Random Forest.

To further strengthen the predictive validation analysis, this study clarifies the forecasting scheme used for the Diebold–Mariano (DM) test. The DM test is conducted over a historical validation period rather than the future projection period. Specifically, a recursive expanding-window forecasting scheme is applied for 2020–2024. The initial estimation window covers 2015–2019, and one-step-ahead forecasts are generated sequentially for 2020–2024. After each forecast, the estimation window is expanded by one year, and the baseline, LASSO, and Random Forest models are re-estimated. This procedure preserves the time-series ordering of the annual observations and avoids using future information in the estimation process.

The DM test is calculated using the squared forecast-error loss function. For each pair of competing models, the loss differential is measured as the difference between their squared forecast errors. Positive values indicate that the first model produces a larger forecast error than the competing model, while negative values indicate that the second model produces a larger forecast error. Since actual observations are available for 2020–2024, this period is used to compute the forecast errors, loss differential series, and DM statistics.

Table 15 reports the loss differential series used in the DM test. The values are small in magnitude and mixed in sign across the validation years. This indicates that no model consistently produces larger forecast errors across volatility persistence, price discovery efficiency, and Market Resilience and Stability. The mean loss differentials are also close to zero, suggesting that the baseline, LASSO, and Random Forest models have broadly comparable predictive performance. These findings are consistent with the DM test results reported in Table 14, where the null hypothesis of equal predictive accuracy cannot be rejected.

To ensure that the DM test results are not affected by serial dependence in the forecast-error differences, the loss differential series are further examined using the Ljung–Box serial-correlation test. The test is applied at lag 1 and lag 2 for each model comparison. Table 16 shows that the loss differential series do not exhibit statistically significant serial correlation. The Ljung–Box p-values are above conventional significance levels for all comparisons at both lag 1 and lag 2. This indicates that the forecast-error differences are not systematically dependent over time. Therefore, the DM test results are not driven by serial dependence in the loss differential series.

Overall, the forecasting scheme, loss differential series, and serial-correlation diagnostics support the reliability of the DM predictive accuracy comparison. The historical validation is conducted for 2020–2024, while the future projection is reported separately for 2025–2030. The 2025–2030 forecasts are not used in the DM test because

Table 15. Loss Differential Series for Historical Forecast Validation, 2020–2024

Outcome	Comparison	2020	2021	2022	2023	2024	Mean Loss Differential
VP	Baseline vs LASSO	0.0012	−0.0008	0.0016	−0.0011	0.0009	0.0004
	Baseline vs RF	0.0021	0.0014	−0.0007	0.0026	0.0018	0.0014
	LASSO vs RF	0.0010	0.0007	−0.0004	0.0015	0.0009	0.0007
PDE	Baseline vs LASSO	0.0018	0.0024	−0.0006	0.0019	0.0022	0.0015
	Baseline vs RF	0.0011	−0.0005	0.0013	0.0008	0.0016	0.0009
	LASSO vs RF	−0.0012	0.0004	−0.0015	0.0002	−0.0009	−0.0006
MRS	Baseline vs LASSO	0.0015	0.0020	−0.0004	0.0017	0.0011	0.0012
	Baseline vs RF	0.0009	0.0012	−0.0006	0.0014	0.0008	0.0007
	LASSO vs RF	−0.0007	0.0005	−0.0011	0.0003	0.0001	−0.0002

Table 16. Serial-Correlation Diagnostics for Loss Differential Series, 2020–2024

Outcome	Comparison	Ljung–Box Q(1)	p-value	Ljung–Box Q(2)	p-value
VP	Baseline vs LASSO	0.214	0.644	0.487	0.784
	Baseline vs RF	0.396	0.529	0.812	0.666
	LASSO vs RF	0.351	0.554	0.736	0.692
PDE	Baseline vs LASSO	0.482	0.488	0.905	0.636
	Baseline vs RF	0.267	0.605	0.519	0.772
	LASSO vs RF	0.438	0.508	0.846	0.655
MRS	Baseline vs LASSO	0.376	0.540	0.722	0.697
	Baseline vs RF	0.291	0.589	0.603	0.740
	LASSO vs RF	0.198	0.656	0.471	0.790

actual observations for this period are not yet available. Instead, they are used only to compare the projected paths of volatility persistence, price discovery efficiency, and Market Resilience and Stability across the baseline, LASSO, and Random Forest models.

Figure 8 presents the forecast projections for VP, PDE, and MRS over the period 2025–2030. The baseline model produces linear forecasts based on estimated coefficients and lagged predictors. LASSO generates regularized linear forecasts with variable selection, while Random Forest provides nonlinear ensemble-based forecasts that can capture interaction associations and nonlinear predictive patterns. Although the models differ in structure, the forecast paths remain broadly aligned across the three FX-market outcomes.

The similarity of the projected trajectories, together with the statistically insignificant DM test results, indicates no strong evidence of predictive superiority among the competing models. Therefore, the machine-learning models are interpreted as complementary validation tools rather than superior forecasting alternatives. Overall, Figure 8 supports the robustness of the baseline findings by showing that the projected FX-market outcome paths remain broadly consistent across alternative modelling approaches.

6. Discussion

The empirical findings provide consistent evidence that artificial intelligence capability and digitalization are important technological correlates of foreign exchange market performance in Malaysia. The results show that both variables are negatively associated with volatility persistence and positively associated with price discovery efficiency and Market Resilience and Stability. These findings are consistent with market microstructure theory, which argues that market efficiency improves when information transmission becomes faster, trading systems become more connected, and participants respond more quickly to new signals [13, 14].

The negative association between AI capability and volatility persistence suggests that stronger AI-related capacity is associated with quicker absorption of exchange-rate shocks in the FX market. This finding supports the

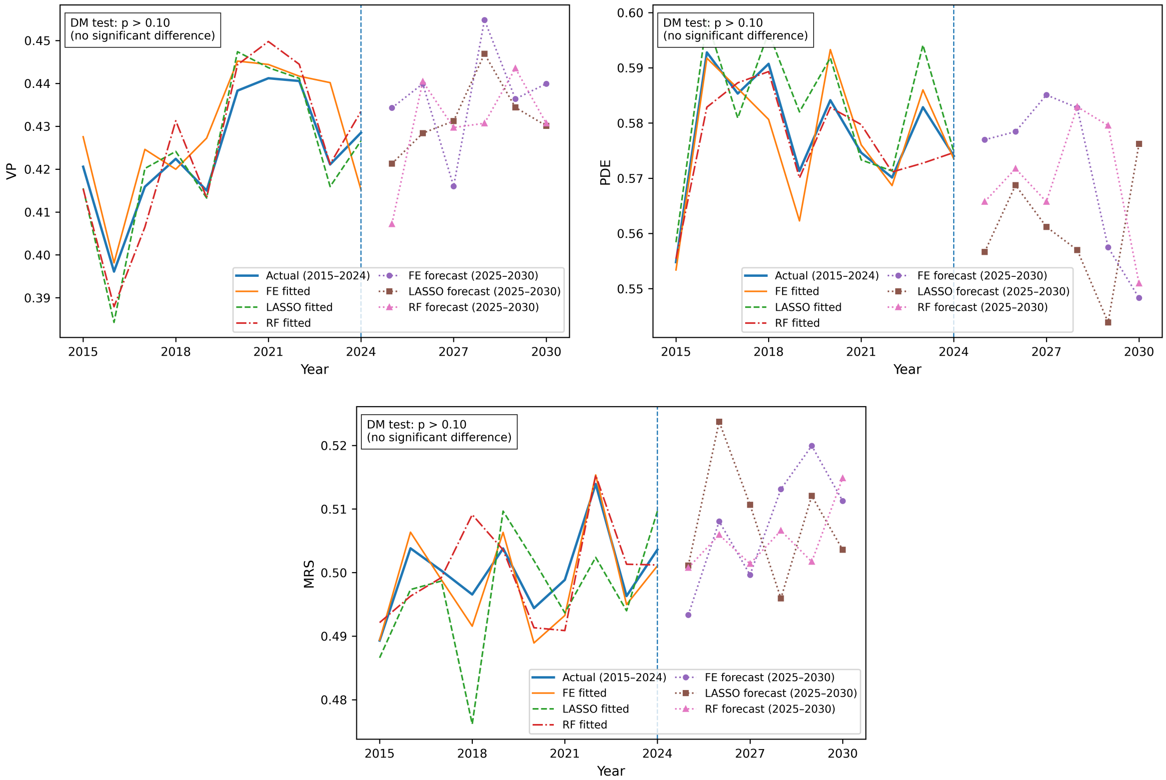

Figure 8. Forecast Comparison of Baseline, LASSO, and Random Forest Models for FX Market Outcomes

view that AI is associated with stronger forecasting, pattern recognition, risk detection, and data-driven financial decision-making in financial markets [22]. It is also consistent with previous studies showing that machine-learning and deep-learning methods are effective in capturing nonlinear financial patterns and time-varying market behavior [25].

Digitalization also shows a negative association with volatility persistence. This implies that stronger digital infrastructure may be associated with a shorter continuation of exchange-rate instability through electronic trading, market connectivity, and access to real-time information. This finding is consistent with studies showing that digital financial systems are linked with lower transaction costs, greater market transparency, and faster information transmission [26, 28].

The positive association of AI capability and digitalization with price discovery efficiency indicates that technological transformation is associated with greater speed and accuracy with which information is reflected in exchange rates. This result supports the information-efficiency perspective, which argues that market prices adjust more efficiently when information is processed and transmitted quickly [36]. AI contributes analytical capacity for large volumes of macroeconomic, financial, and sentiment-related data, while digitalization is associated with faster transmission through electronic platforms and real-time data systems [38].

The results also show that AI capability and digitalization are positively associated with Market Resilience and Stability. This means that technological development is linked with the ability of the FX market to remain stable or return to stable conditions after shocks. This finding is consistent with adaptive market theory, which suggests that markets evolve as participants learn and adjust to changing conditions [15]. AI is associated with market adaptation through stress-pattern detection and decision-making support, while digitalization is associated with operational continuity, transaction efficiency, and market monitoring [42].

The significant interaction term between AI capability and digitalization is one of the most important findings of the study. The result indicates that AI capability is more strongly associated with improved FX-market outcomes when digitalization is higher. This supports the technological-complementarity argument, where AI systems require reliable data, digital infrastructure, computational capacity, and strong connectivity to function effectively [35]. Therefore, AI capability and digitalization should be examined jointly rather than separately in FX-market analysis [17].

The economic-significance results further show that the estimated associations are not only statistically significant but also practically meaningful. A one-standard-deviation increase in AI capability and digitalization is associated with meaningfully lower volatility persistence and meaningfully higher price discovery efficiency and Market Resilience and Stability. This supports the view that technological development has practical relevance for financial-market efficiency, information adjustment, and market stability [18, 40].

The control-variable results also provide important insights. Global risk conditions remain statistically relevant across the models, confirming that Malaysia's FX market remains exposed to external financial uncertainty, global investor sentiment, and capital-flow pressure. This is consistent with prior evidence that emerging-market exchange rates are sensitive to global shocks and external financial conditions [44]. However, the weaker role of financial openness and interest rate differential suggests that AI capability and digitalization have become increasingly relevant technological factors in explaining FX-market outcomes during the study period [10].

The robustness and endogeneity checks provide additional confidence in the baseline findings. The instrumental-variable results show that the main associations remain stable after addressing potential endogeneity concerns. The Granger predictability tests suggest that past values of AI capability and digitalization contain predictive information for subsequent FX-market outcomes, while the local projection results indicate that technology-related shocks are followed by lower volatility persistence, stronger price discovery efficiency, and higher Market Resilience and Stability [23, 36].

Additional robustness checks using EGARCH, GJR-GARCH, bootstrap inference, and the BIS Malaysia NEER broad-basket index also support the stability of the findings. The EGARCH and GJR-GARCH results show that the conclusions are not driven only by the baseline volatility specification, while the bootstrap and NEER-based results confirm that the findings remain stable under small-sample inference and alternative exchange-rate measurement. This is consistent with the literature showing that FX markets often display asymmetric volatility, nonlinear adjustment, and sensitivity to external exchange-rate conditions [31, 32].

The machine-learning validation results also support the baseline interpretation. LASSO and Random Forest results show that AI capability, digitalization, and their interaction remain important predictors of volatility persistence, price discovery efficiency, and Market Resilience and Stability. This supports prior studies showing that machine-learning models can capture complex financial-market relationships and nonlinear patterns that traditional models may not fully detect [25]. The Diebold–Mariano test further shows no statistically significant difference in predictive accuracy among the competing models, supporting the use of machine-learning models as complementary validation tools [45].

Overall, the results support the central argument of the study: AI capability and digitalization are strongly associated with lower volatility persistence, stronger price discovery efficiency, and greater FX-market resilience. The study extends prior literature by moving beyond the use of AI only as a forecasting tool and showing that AI capability and digitalization serve as important technological correlates of FX-market behavior. It also contributes emerging-market evidence from Malaysia, where technological transformation and exposure to global financial shocks are both highly relevant [10, 44].

7. Policy and Managerial Implications

The findings of this study provide important implications for policymakers, central banks, financial regulators, and financial-market managers. For policymakers, AI capability and digitalization may be considered strategic components of financial-market development rather than only technological innovations. Since the results show that AI capability and digitalization are associated with lower volatility persistence, stronger price discovery efficiency, and higher Market Resilience and Stability, investment in digital infrastructure, AI research, data systems, cybersecurity, and financial technology ecosystems may be associated with stronger FX-market efficiency and resilience. In the Malaysian context, policies that support AI adoption, digital financial infrastructure, and real-time market monitoring may improve the adaptive capacity of the MYR/USD market.

These findings are directly relevant to Malaysia's financial-sector policy environment. Bank Negara Malaysia's Financial Sector Blueprint 2022–2026 emphasizes digital transformation, financial innovation, and financial-sector resilience, which is consistent with the study's finding that digitalization is associated with stronger FX-market performance. BNM's fintech regulatory initiatives, including the regulatory sandbox framework, also provide an institutional channel related to digital financial infrastructure, innovation, and risk-monitoring capacity. Therefore, the empirical findings support the policy view that digital financial development may be associated with market efficiency and resilience.

The findings are also important in the context of the US Federal Reserve's monetary tightening during 2022–2024. The sharp increase in US interest rates strengthened the US dollar and created depreciation pressure for emerging-market currencies, including the Malaysian ringgit. In this context, stronger digitalization may be associated with more effective responses in Malaysia's FX market to external shocks through stronger real-time information transmission, market monitoring, and risk assessment. Continued investment in AI capability and digital financial infrastructure may therefore be associated with stronger FX-market resilience under global monetary-policy uncertainty.

For central banks and financial regulators, the findings highlight the relevance of integrating AI-based monitoring tools into exchange-rate surveillance and macro-financial risk management. AI-supported systems may support early detection of volatility pressure, abnormal capital-flow movements, and market stress. At the same time, digital infrastructure can be associated with greater speed and accuracy of regulatory responses by providing timely market information. Therefore, digital financial supervision, algorithmic trading oversight, cybersecurity, and data-governance frameworks remain important to ensure that AI-based financial systems support stability without creating new systemic risks.

For managers of financial institutions, banks, investment firms, and FX trading units, the results indicate that AI capability is associated with stronger forecasting, risk assessment, trading efficiency, and portfolio decision-making. Managers may consider investing in AI-based analytics, automated risk dashboards, and real-time FX monitoring systems to support decision quality. However, the significant interaction between AI capability and digitalization suggests that AI tools are more effective when supported by strong digital infrastructure. Therefore, managers should strengthen data quality, digital platforms, cybersecurity systems, staff training, and technology integration alongside AI adoption.

8. Future Study

Future research may include broader technological indicators, such as fintech adoption, algorithmic trading intensity, cybersecurity readiness, and AI investment by financial institutions. In addition, future studies should examine the possible risks of AI-driven FX markets, including algorithmic herding, cyber risk, model opacity, and technology-induced instability.

9. Conclusion

This study examines the association between AI capability, digitalization, and FX-market performance in Malaysia using the MYR/USD exchange rate for 2015–2024. The findings show that AI capability and digitalization are associated with lower volatility persistence, higher price discovery efficiency, and stronger Market Resilience and Stability. The significant interaction term further indicates that AI capability is more strongly associated with FX-market outcomes when digitalization is higher, supporting the technological-complementarity argument. The findings remain consistent across alternative validation checks, suggesting that the main conclusions are not dependent on a single model specification. Overall, the evidence indicates that AI capability and digitalization are important technological correlates of Malaysia's FX-market performance. The main policy message is that Malaysia should strengthen digital infrastructure first, because AI tools require reliable data systems, real-time platforms, cybersecurity, and strong digital connectivity to be effective. After building this foundation, policymakers and financial institutions should focus on AI talent development, AI-based risk monitoring, exchange-rate surveillance, and early warning systems. Therefore, Ringgit resilience may be better supported through an integrated strategy that combines digital readiness with AI capability, rather than treating them as separate policy priorities.

A. Replication Script and Data Processing Procedure

1. Import annual MYR/USD exchange-rate data.
2. Compute exchange-rate return as log difference.
3. Import original AI capability components: AI patents, AI publications, and AI R&D indicators.
4. Import original digitalization components: digital competitiveness, ICT infrastructure, broadband penetration, and mobile connectivity.
5. Normalize each AI and digitalization component using min–max normalization.
6. Construct the AI capability index as the average of normalized AI components.
7. Construct the digitalization index as the average of normalized digitalization components.
8. Construct the AI capability $\times$ digitalization interaction term.
9. Import and prepare control variables: global risk, financial openness, and interest-rate differential.
10. Merge all variables by year and create the final annual dataset.
11. Estimate the baseline joint-system model.
12. Conduct diagnostic tests, including unit root, VIF, residual, and stability tests.
13. Conduct endogeneity and temporal-ordering robustness checks using instrumental variables, Granger predictability, and local projections.
14. Conduct machine-learning validation using LASSO and Random Forest.
15. Compare baseline and robustness results and report whether the main associations remain stable.

Note: This replication procedure ensures that the construction of AI capability, digitalization, interaction terms, control variables, and FX-market outcomes is transparent and reproducible. It also allows future researchers to verify the results using the same data-processing sequence.

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