“What drives central bank digital currency implementation? A machine-learning analysis using support vector machines and SHAP explainability”

AUTHORS

Zhanat Khishauyeva
Diana Sitenko
Vitaliia Koibichuk
Arsen Petrosyan
Gaukhar Kodasheva
Ekaterina Dmitrieva
Kseniia Mohylna

ARTICLE INFO	Zhanat Khishauyeva, Diana Sitenko, Vitaliia Koibichuk, Arsen Petrosyan, Gaukhar Kodasheva, Ekaterina Dmitrieva and Kseniia Mohylna (2026). What drives central bank digital currency implementation? A machine-learning analysis using support vector machines and SHAP explainability. *Banks and Bank Systems*, *21*(1), 173-191. doi: 10.21511/bbs.21(1).2026.13
DOI	http://dx.doi.org/10.21511/bbs.21(1).2026.13
RELEASED ON	Monday, 23 March 2026
RECEIVED ON	Monday, 02 February 2026
ACCEPTED ON	Monday, 09 March 2026
LICENSE	This work is licensed under a Creative Commons Attribution 4.0 International License
JOURNAL	"Banks and Bank Systems"
ISSN PRINT	1816-7403
ISSN ONLINE	1991-7074
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
68	4	3

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

Zhanat Khishauyeva (Republic of Kazakhstan), **Diana Sitenko** (Republic of Kazakhstan),
Vitaliia Koibichuk (Ukraine), **Arsen Petrosyan** (Armenia),
Gaukhar Kodasheva (Republic of Kazakhstan), **Ekaterina Dmitrieva** (USA),
Kseniia Mohylna (Ukraine)

WHAT DRIVES CENTRAL BANK DIGITAL CURRENCY IMPLEMENTATION? A MACHINE-LEARNING ANALYSIS USING SUPPORT VECTOR MACHINES AND SHAP EXPLAINABILITY

Type of the article: Research Article

Received on: 2nd of February, 2026
Accepted on: 9th of March, 2026
Published on: 23th of March, 2026

Zhanat Khishauyeva, Ph.D., Assoc. Prof., Y.A. Buketov Karaganda National Research University, Republic of Kazakhstan.

Diana Sitenko, Ph.D. in Economics, Professor, Economic Faculty, Y.A. Buketov Karaganda National Research University, Republic of Kazakhstan.

Vitaliia Koibichuk, Ph.D., Assoc. Prof., Head of Economic Cybernetics Department, Sumy State University, Ukraine.

Arsen Petrosyan, Ph.D., Assoc. Prof., Head of the Educational Division, Armenian State University of Economics, Armenia.

Gaukhar Kodasheva, Ph.D. in Finance, Acting Associate Professor, L.N. Gumilyov Eurasian National University, Republic of Kazakhstan. (Corresponding author)

Ekaterina Dmitrieva, Investor Relations Expert in Alternative Investments, Columbia Business School, USA.

Kseniia Mohylna, Student, Economic Cybernetics Department, Sumy State University, Ukraine.

Abstract

Central bank digital currency (CBDC) programs have rapidly shifted from experimentation to policy-critical infrastructure decisions, yet countries show strikingly uneven progress from research to pilots and implementation. This study aims to identify and explain the key structural, macroeconomic, technological, and ecosystem-related factors that differentiate CBDC initiatives advancing to pilot or implementation stages from those remaining in early research or being discontinued across countries worldwide. Using 161 CBDC projects across 109 countries (as of December 2024) and 10 project-, public interest-, technology-, and macroeconomic indicators, we estimate a Support Vector Machines classifier with GridSearchCV (5-fold) tuning and interpret the results using Shapley Additive exPlanations explainability. The raw outcome distribution was strongly imbalanced (83.85% in the early/cancelled class), so ADASYN balancing was applied, producing 270 observations with equal class shares and an 85/15 train–test split (229/41). The optimized SVM (RBF; C = 10, gamma = 10) achieved 93.90% cross-validated accuracy and 0.88 accuracy on the test set, indicating strong predictive performance on unseen data. Test-set metrics show an informative error profile: for class 1 (advanced projects), recall = 1.00 and F1 = 0.89, while for class 0 (early/cancelled), precision = 1.00 with recall = 0.75 (macro/weighted F1 = 0.88), implying that the model identifies all advanced projects but may misclassify around one-quarter of early/cancelled cases. SHAP ranks the strongest drivers as use-case direction, inflation, crypto adoption ranking, CBDC-related research output, and international participation, with mixed/wholesale projects, higher inflation, stronger scientific attention, and greater international involvement generally increasing the likelihood of advancement.

Keywords central bank digital currency, cryptocurrency, digitalization, inflation, machine learning, SVM, SHAP

JEL Classification E42, E58, O33, C45

INTRODUCTION

Central bank digital currency (CBDC) has evolved from a largely exploratory idea to a mainstream policy agenda, with international institutions framing it as a strategic response to the rapid shifts in the payments landscape, the expansion of privately issued digital money, and rising expectations for fast, low-cost, and resilient digital payments. The IMF has recently synthesized global progress and outstanding design questions, emphasizing that CBDC decisions increasingly sit at the intersection of monetary sovereignty, payment-system resilience, inclusion, and financial stability, rather than being

Conflict of interest statement:
Author(s) reported no conflict of interest

a purely technological upgrade (IMF, 2024). At the same time, the BIS survey evidence shows that CBDC work has become near-universal among central banks: in 2024, 91% of surveyed central banks reported exploring retail and/or wholesale CBDCs, with wholesale initiatives, on average, at more advanced stages (Illes et al., 2025).

Policy urgency is reinforced by the fact that CBDC outcomes vary widely. While some jurisdictions have advanced to pilots and early deployments, many others remain in the research stage or discontinue initiatives, suggesting that progress depends on country-specific conditions and project choices. The IMF paper explicitly notes the importance of adoption strategies and ecosystem readiness, covering intermediaries, users, and practical implementation frictions, highlighting that CBDCs succeed only when institutional capacity and stakeholder incentives align (Koonprasert et al., 2024). Complementing this view, the OECD underlines that CBDCs carry broad domestic and international implications (including cross-border payments and market structure) and that legitimacy hinges on trust-related design attributes such as privacy, equitable access, and democratic values (Demmou & Sagot, 2021).

In Europe, the "actuality" is particularly pronounced because the digital euro has become a live legislative and strategic project, linking payments sovereignty with the EU's regulatory and competitiveness agenda. The ECB's ongoing reporting on the digital euro preparation phase (and its explicit linkage to the European Commission's draft regulation) illustrates that major economies are moving from conceptual debate to concrete governance, design, and implementation planning (ECB, 2025). Recent reporting also indicates that EU institutions are actively negotiating key features, including online/offline functionality, usage limits, and the overall legal framework, suggesting that CBDCs are entering a decisive policy window where design trade-offs will influence real-world implementation trajectories (Reuters, 2025).

Against this background, understanding why some CBDC initiatives progress from research to proof of concept, pilot, and eventual implementation is central. Although major policy and institutional reports increasingly map design principles, technological architectures, and regulatory risks, they provide limited empirical insight into which combinations of public interest, technological readiness, macroeconomic pressures, research capacity, and international cooperation most consistently distinguish more advanced CBDC projects from early-stage initiatives. A systematic data-driven assessment of these factors across a broad international sample is therefore needed to clarify the relative importance of structural, institutional, and technological drivers of CBDC advancement. Such evidence can contribute to a more nuanced understanding of cross-country heterogeneity and inform the development of more targeted and context-sensitive CBDC strategies and implementation pathways.

1. LITERATURE REVIEW

The implementation of CBDC projects is increasingly understood as an outcome of broader digital transformation capacity rather than a purely monetary-technical choice. Progress in digital finance depends on the maturity of national banking and financial ecosystems, which tend to cluster by income level and digitalization pathways, implying that CBDC readiness is structurally heterogeneous across countries (Abbasova et al., 2025). Similar heterogeneity is observed in sector-level transformation readiness, suggesting that institutional capability, technology absorption, and governance routines influence the speed at which complex innovations can transition from concept to deployment (Al-Smadi, 2025). Because CBDCs are state-led payment infrastructures, the quality of public-sector digital governance and managerial competencies becomes a direct enabling constraint, particularly in the European context, where governance models and competencies vary across administrations (Androniceanu & Streimikiene, 2025). The ability to meet digital policy goals also depends on population-level digital competences, where distinct "profiles" of competence alignment can translate into different adoption and implementation trajectories for

http://dx.doi.org/10.21511/bbs.21(1).2026.13

public digital services and, by extension, CBDC infrastructures (Dečman et al., 2025). Evidence from European economy mapping further supports that digital transformation follows recognizable national patterns, strengthening the expectation that CBDC advancement is shaped by latent digital-development regimes rather than a single determinant (Pakhnenko et al., 2025).

The advancement of CBDC projects also intersects with financial inclusion, banking stability, and consumer finance innovation, as CBDCs can alter access channels, intermediation, and the competitive landscape of payment services. Digital finance and inclusion have been linked to banking stability in international evidence, indicating that "more digital" financial systems are not automatically riskier and may support stability under certain institutional conditions (Anton & Afloarei Nucu, 2024). At the retail edge, alternative digital credit models and LendTech solutions (including BNPL) show how rapidly user-facing digital financial products can scale during shocks, highlighting the importance of user experience, distribution channels, and complementarity with existing banking services, factors that CBDC designs must accommodate to move beyond pilots (Waliszewski et al., 2024). Adoption decisions in digital banking are consistently tied to perceived usefulness, ease of use, and self-efficacy, implying that CBDC uptake, and therefore implementation success, depends on behavioral frictions and capability gaps, not only on legal readiness (Hedau, 2025). Broader behavioral determinants similarly shape intention to adopt digital financial services, reinforcing that CBDC "implementation" must be treated as an ecosystem adoption problem rather than a narrow IT deployment (Soussou & Hamrouni, 2025). The evolution of fintech business models and digital economy drivers also indicates dynamic competitive pressure that can either accelerate CBDC development (as a public option) or slow it down (if private solutions dominate), depending on the national context (Polishchuk, 2023).

A central strand of the landscape concerns the relationship between CBDCs and crypto-asset ecosystems, where private digital money affects both policy urgency and design trade-offs. Willingness to purchase or use cryptocurrency in emerging contexts is shaped by individual-level determinants that can either complement CBDC adoption (digital familiarity) or compete with it (preference for decentralized alternatives) (Islam et al., 2024). Crypto markets also display herding behavior and sentiment-driven dynamics, underscoring why central banks may prioritize a trusted public digital payment instrument in environments where speculative cycles and information cascades are salient (Gherghina & Constantinescu, 2024). Shocks such as the COVID-19 pandemic have been associated with changing patterns of crypto adoption in investment behavior, suggesting that crisis periods can accelerate digital-asset diffusion and thereby influence CBDC policy trajectories (Niftiyev & Kheyirkhabarli, 2024). Portfolio and safe-haven considerations in crypto markets (including gold-backed crypto instruments) further show that digital assets are increasingly entering mainstream risk management, shaping the "baseline" against which CBDCs are evaluated by households and institutions (Maghyereh et al., 2025). At the systemic level, connectedness between DeFi assets and traditional financial sectors implies that CBDCs will be implemented into an increasingly intertwined digital financial system, where spillovers and interdependencies matter for policy design and stakeholder buy-in (Huang & Hsu, 2025). Research also indicates that the next phase of crypto market analysis increasingly relies on machine learning and the fusion of technical and behavioral indicators, reinforcing the relevance of advanced predictive analytics for understanding digital currency dynamics (Máté et al., 2024).

Macroeconomic and monetary conditions form another set of drivers, because CBDC priorities often intensify when monetary stability, inflation dynamics, or currency-market pressures become politically and economically salient. Monetary stability and central bank independence are empirically interlinked, implying that countries with stronger institutional independence may possess both the credibility and operational capacity to sustain long, multi-stage CBDC programs (Tanriverdi et al., 2024). The broader macroeconomic environment, including unconventional monetary policies, affects liquidity, financial conditions, and risk-taking, which can shape institutional incentives and the perceived need for new monetary instruments (Jabiyev et al., 2025). Exchange-rate turbulence and the realities of central bank interventions underscore that currency dynamics remain a live operational challenge, which can influence whether CBDCs are framed as tools for resilience, sovereignty, or enhanced monetary transmission (Yoshimori, 2025). In parallel, climate-related challenges are increasingly discussed in central banking strategy, suggesting that CBDC projects may also be influenced by evolving mandates and institutional priorities that compete for attention and resources (Omeir & Vasiliauskaite, 2025).

Implementation readiness is also conditioned by trust, privacy expectations, and institutional legitimacy, issues that are especially decisive once projects shift from technical pilots to public deployment. Heterogeneity in privacy preferences and trust in central banks implies that CBDC design choices (privacy-by-design, data governance, and user protections) can directly determine political feasibility and user acceptance, thereby affecting implementation outcomes (Koziuk et al., 2025). Wider evidence on digital governance highlights its role in building antifragile public-sector capabilities, suggesting that resilient governance systems are better positioned to manage the risks, iterative learning, and stakeholder coordination required in CBDC rollouts (Bartuseviciene & Butkus, 2024). The expansion of machine learning on social media and the associated privacy risks demonstrate that user awareness and security concerns are non-trivial and can spill over into attitudes toward state digital infrastructures, making privacy governance a key determinant of practical implementation (Wieczorek & Postrzednik-Lotko, 2025). These insights align with broader discussions on AI readiness, ethics, institutions, and infrastructure as key drivers of banking transformation, suggesting that the legitimacy of technology and institutional trust are foundational for CBDC adoption and scaling (Sitnicka et al., 2025; Tarasenko et al., 2022).

The security, integrity, and transparency of the financial system provide additional motivation and constraints for CBDC projects, especially where illicit finance risks or cyber threats are heightened. Global patterns of digital convergence indicate that cybersecurity, business transparency, and AML efficiency co-evolve with digital transformation, suggesting that CBDC implementation is more likely to progress where integrity institutions can maintain a secure and compliant digital ecosystem (Kuzior et al., 2022; Klochan & Filipov, 2023). The relationship between financial digitalization, shadow economy dynamics, and financial stability further suggests that CBDCs may be viewed as instruments to reduce informality and strengthen traceability; however, weak institutional settings may face stability risks when digitization accelerates (Bozhenko et al., 2024). Country clustering by FATF compliance and effectiveness reveals that AML/CFT capacity differs systematically, which can impact both the feasibility of CBDC compliance architectures and the political appetite for programmable controls (Kuzior et al., 2025). Wartime and crisis contexts intensify cyberattacks and financial fraud risks, demonstrating that judicial-system maturity and enforcement capacity can become binding constraints for any national-scale digital payment infrastructure, including CBDCs (Yarovenko et al., 2024a). This connects to the expanding literature on AI and machine learning for combating illegal financial operations, which underscores that analytic capability is increasingly central to financial integrity strategies that may complement CBDC infrastructures (Lyeonov et al., 2024a). Evidence on AI's dual-use potential, which benefits AML services but also potentially empowers criminals, highlights that CBDC implementation must anticipate adaptive adversaries and invest in oversight capabilities (Lyeonov et al., 2025). Operationally oriented work using classifiers to analyze cryptocurrency transactions further demonstrates that scalable analytics can support risk-based controls in digital-money ecosystems that increasingly interact with CBDCs (Lyeonov et al., 2024b). Complementary bibliometric evidence on transparency research trends in insurance markets and on bank capital management indicates that governance and prudential themes remain central as finance digitizes, reinforcing that CBDCs sit inside a wider stability-and-transparency research agenda (Kuzior et al., 2023; Ashurbayli-Huseynova & Garmidarova, 2025).

Technological infrastructure choices and innovation diffusion mechanisms also shape implementation. Blockchain applications and their research evolution in insurance illustrate both the promise and the complexity of deploying distributed-ledger solutions in regulated sectors, offering lessons for CBDC architectures (including permissioned

http://dx.doi.org/10.21511/bbs.21(1).2026.13

DLT variants) (Eletter, 2024). Technical work on blockchain hash algorithm testing underscores that cryptographic design quality is a core precondition for secure digital-value systems, which is particularly relevant for CBDC platforms and interoperability layers (Kuznetsov et al., 2019). Blockchain-enabled leadership and e-commerce transformation evidence shows that organizational leadership can be a decisive mediator in moving from experimentation to operational use. This pattern plausibly extends to CBDC programs requiring multi-stakeholder coordination and vendor ecosystems (Mouna & Yassine, 2024). The policy environment is also increasingly requiring a link between technology and public integrity outcomes; knowledge and technology have been modelled as determinants of corruption reduction, aligning with the argument that CBDCs may be positioned as transparency-enhancing infrastructures in certain institutional contexts (Yefimenko et al., 2025). Digital transformation evidence in local public finance management shows that implementation bottlenecks (skills, process redesign, and accountability) recur even in smaller-scale systems, offering a cautionary analog for CBDC programs that must integrate with fiscal, welfare, and municipal payment flows (Jumaiyah et al., 2025). Related evidence that "value for money" concepts improve budget performance supports the practical view that CBDC implementation will be judged not only on technical success but also on demonstrable efficiency and public value creation (Said et al., 2025).

Given this multidimensional landscape, CBDC-specific scholarship increasingly synthesizes adoption patterns and country characteristics, but still leaves room for integrative, evidence-based prediction and explanation of implementation outcomes. Global reviews of CBDC trends highlight variation in adoption, inclusion goals, and country characteristics, implying that implementation is contingent on national contexts rather than governed by a universal pathway (Koparan, 2025). Comparative examinations that juxtapose CBDCs with alternative "future finance" narratives reflect the breadth of expectations and misconceptions surrounding CBDCs, reinforcing the need for empirically grounded assessments of what actually drives project progression (Shafranova et al., 2024). Across the broader digital economy, research trend mapping, including studies of online shopping behavior, shows that adoption ecosystems are shaped by technology diffusion, trust, and behavioral responses in "Industry 4.0" environments, which parallels the adoption challenge faced by CBDCs (Xuan et al., 2025). Perceptions of AI futures, ranging from fear to hope, further suggest that societal attitudes toward advanced technologies can influence the acceptance of state-led digital infrastructures, adding another layer to the feasibility of CBDC implementation (Yarovenko et al., 2024b). Finally, the increasing use of machine-learning methods to integrate economic indicators, ESG factors, and sentiment in currency-related analytics underscores why explainable ML frameworks are becoming suitable tools for policy-relevant prediction, especially when the aim is not only accuracy but transparent drivers (Banerjee, 2025). Growing demands from financial institutions for transparency and accountability, together with ESG disclosure requirements arising from tightening regulation and heightened scrutiny of reputational assessment, make artificial intelligence an integral component of modern financial systems. When properly configured, AI accelerates information processing and enhances relevance and accuracy; however, it also requires strict oversight and clearly defined boundaries of use, especially in light of regulatory, legal, and reputational risks. Modeling financial threats and opportunities under geopolitical shocks also supports the idea that complex, non-linear environments may benefit from robust predictive approaches rather than single-equation intuition (Pozovna et al., 2025).

Digital disruption evidence from other high-stakes sectors underscores a final implementation lesson: progress often accelerates when external shocks align incentives and remove organizational inertia, but bottlenecks persist when socio-ecological barriers and digital divides remain unresolved (Conley, 2025; Sidii, 2025). The use of advanced digital tools (drones, GIS, satellites) in emergency response demonstrates that implementation success hinges on interoperability, governance, and capability building, conditions directly comparable to national CBDC infrastructures that must integrate across institutions and services (Mercer-Bey, 2025).

Prior research indicates that CBDC implementation is driven by interacting layers of digital governance capacity, financial ecosystem maturity, macro-monetary conditions, integrity and cybersecurity readiness, and behavioral trust and privacy constraints, with strong cross-country heterogeneity. At the same time, the literature remains fragmented across domains and often descriptive, providing limited integrative evidence on the relative importance of these drivers for advancing real-world CBDC projects. This motivates the use of explainable machine-learning approaches to jointly model non-linear interactions while retaining policy interpretability, aligning directly with an SVM–SHAP framework for identifying the most influential determinants of CBDC project implementation.

The aim of this study is to identify and explain the key structural, macroeconomic, technological, and ecosystem-related factors that differentiate CBDC initiatives advancing to pilot or implementation stages from those remaining in early research or being discontinued across countries worldwide.

2. METHODOLOGY

The study uses a systematic approach to collecting, preparing, and analyzing data to identify factors influencing the implementation of central bank digital currency (CBDC) projects. The main source of data on CBDC projects was the CBDC tracker platform, which aggregates up-to-date information on initiatives related to central bank digital currencies. In total, data were collected on 161 observations, i.e., CBDC projects at various stages of development in 109 countries worldwide as of the end of 2024 (Appendix A). The dependent variable of the dataset is a binary variable y, indicating the degree of project implementation. The dataset also contained 10 independent variables characterizing social, technological, economic, and other factors related to the implementation of CBDC projects. A complete list, description, and sources of information for the variables in the dataset are described in more detail in Table 1.

To model the status of CBDC project implementation, the support vector method was chosen due to its ability to work effectively with small samples and high feature space dimensions, which is important for this study, as the initial dataset contains only 161 observations and 10 independent variables. Also, unlike traditional linear models, SVM does not require strict assumptions about data distribution, which is also useful. In addition, the support vector method allows complex separating surfaces to be constructed using kernel functions, which can be non-linear, which is particularly important in the context of CBDC projects, where the interaction of economic, technological, and social factors is often non-linear. These characteristics make the support vector method an optimal tool for analyzing the success factors of CBDC projects in the context of available data.

Before starting the modelling, an important step was to prepare the collected data set, in particular by scaling the independent variables. Analysis of the descriptive statistics in Table 2 shows significant differences in the scales of the variables in the initial dataset. For example, variable x_7 (country GDP) has an average value of around 10^{12}, while variable x_4 (telecommunications infrastructure index) ranges from 0 to 1. Given that the selected modelling method (support vector method) is based on calculating distances between points in a multidimensional space, where different variable scales can distort the results, to avoid the domination of variables with larger numerical values over those with smaller scales, the variables in the set were scaled using the MinMaxScaler method. This procedure brought all variables to the range [0, 1] by calculating according to formula (1), which ensured an equal contribution of all variables to the model training process.

$$x_i^{'} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}, \tag{1}$$

where $x_i^{'}$ – scaled value of feature x for the i-th observation; x_i – initial value of feature x for the i-th observation; $x_{\min}$ – minimum value of feature x; $x_{\max}$ – maximum value of feature x.

Based on the formed training sample, a model was constructed using the support vector machine (SVM) method with the sklearn.svm module from the sklearn library for Python. The main idea of SVM is to find the optimal hyperplane that

http://dx.doi.org/10.21511/bbs.21(1).2026.13

Table 1. Variables of the initial dataset

Indicator	Label	Variable	Data source
Project features	y	Status of the CBDC project as of December 2024. 1 or 0, where 1 means that the project is at the stage of proof of concept, pilot or full implementation, and 0 means that the project has been cancelled or is at the stage of early research	CBDC tracker (2024)
	x_3	Number of years that have passed since the first announcement of this CBDC project	CBDC tracker (2024)
	x_8	Number of CBDC projects started by the country as of the year of the announcement of the relevant CBDC project.	CBDC tracker (2024)
	x_9	Number of international CBDC projects in which the country of origin of the CBDC project participates	CBDC tracker (2024)
	x_{10}	Direction of use of the CBDC project. Can take on 4 values: 1 (retail), 2 (retail and wholesale), 3 (wholesale) or 0 (others)	CBDC tracker (2024)
Public interest	x_1	The number of research papers related to the terms "central bank digital currency" or "CBDC" published in the Scopus science-based database as of December 2024 for the relevant country of origin of the CBDC project	Elsevier (n.d.)
	x_2	Popularity among users of the CBDC's country of origin of the Central Bank Digital Curriculum project search term over the past 5 years, including regions with a low volume of searches. The values range from 0 to 100, where 100 represents the country with the highest popularity relative to the total number of searches, and 0 indicates a place where there is little data on this search term.	Google Trends (2024)
Technological development	x_4	Telecommunications infrastructure index of the project's CBDC country of origin in 2024. 0 to 1 (external indicator extracted from the UN e-Gov Survey)	UN E-Government Knowledgebase (2024)
	x_5	Ranking of the project's CBDC country of origin by the cryptocurrency acceptance index (overall index rating) as of 2024. 1 to 151, where 1 is the maximum use of different types of cryptocurrency services, and 151 is the minimum use of different types of cryptocurrency services	The 2024 Geography of Crypto Report
State of the economy	x_6	Inflation in the country of origin of the CBDC project in consumer prices (annual %) as of 2023	Data bank world development indicators (2023)
	x_7	GDP of the CBDC project's country of origin (in current US dollars) as of 2023	Data bank world development indicators (2023)

maximizes the margin between classes in a multidimensional feature space. Mathematically, for a linear kernel function, this task boils down to a linear minimization problem, which is defined by formula (2):

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i \to \min \tag{2}$$

under the following conditions:

$$y_i\left(w \cdot x_i + b\right) \geq 1 - \xi_i,\ \xi_i \geq 0,$$

where w – weight vector that determines the orientation of the hyperplane; b – shift, displacement; ξ_i – variable errors; and C – regularization parameter.

For nonlinear cases, SVM uses kernel functions that map the input data to a higher-dimensional space where the classes become linearly separable. Among the kernel functions, the most common choices are between linear, polynomial, and RBF kernels. In addition to choosing the basis function for the support vector method, the regularization parameter C is important, which determines the compromise between maximizing the margin and minimizing classification errors on the training sample: smaller values of C create a wider margin by allowing some classification errors, while models with larger C values tend to correctly classify a relatively larger number of observations in the training data. The last important hyperparameter of the model is gamma, which determines the radius of influence of a single training observation, i.e., the extent to which the model 'delves' into the details of explaining each observation.

Thus, the selection of appropriate hyperparameters, including C (regularization), gamma (sensitivity to individual errors in the test sample), and kernel (kernel type), is an important issue when building a model using the support vector method. In this study, the GridSearchCV method was used to select the optimal hyperparameters for the test data sample. It is a technique for selecting the optimal model hyperparameters by enumerating the specified combinations of parameters and evaluating the accuracy of the model for each of them.

This approach to parameter enumeration was implemented using sklearn.model_selection module for Python.

GridSearchCV uses k-fold cross-validation to objectively evaluate each combination of hyperparameters. In this method, the training sample is divided into k equal parts (folds). The model is trained k times, each time using (k – 1) folds for training and one fold for validation. The average accuracy across all k iterations is used as an estimate of the effectiveness of a given combination of hyperparameters. In this study, 5-fold cross-validation (k = 5) was used, which is standard practice for medium-sized datasets. Mathematically, the model performance estimate using the cross-validation method is calculated using formula (3).

$$CV_{score} = \frac{1}{k}\sum_{i=1}^{k} Score\left(M_i, D_i^{val}\right), \tag{3}$$

where CV_{Score} – average model accuracy assessment based on cross-validation results; k – number of folds (in this study, $k = 5$); M_i – a model trained on all folds except the i-th one; D_i^{val} – i-th validation fold; Score (M_i, D_i^{val}) – assessment of the accuracy of the model M_i on the validation fold D_i^{val}.

Since the model is built using the support vector method and does not provide direct coefficients of feature importance, the SHAP (SHapley Additive exPlanations) method was used to assess their impact on the classification result. The SHAP method is based on Shapley's theory of cooperative games and explains the impact of each factor on the model's prediction. It calculates the contribution of each feature to a specific prediction, taking into account all possible combinations of features. Thus, each influence of feature (i) is calculated by sampling different subsets of features (z'), evaluating the influence of this feature, present or absent in the subset, and creating a weighted average value of these influences (Dunbar, 2023). This principle is reflected in formula (4).

$$\Phi_i(f, x) = \sum_{z' \subseteq x'} \frac{|z'|!\left(M - |z'| - 1\right)!}{M!}\left[f_x(z') - f_x\left(\frac{z'}{i}\right)\right], \tag{4}$$

where $\Phi_i(f, x)$ – SHAP value reflecting the contribution of the i-th feature to the model prediction f for observation x; z' – a subset of features that does not contain the feature i; x' – vector of values of all features for a specific observation; M – total number of features in the model; $|z'|$ – number of features in the subset z'; $f_x(z')$ – value of the predictive function when using only features from the subset z'; $f_x(z'/i)$ – model forecast after adding the i-th feature to the subset of factor features.

Thus, the research methodology involves collecting and preparing statistical data on the implementation of CBDC projects and using modern machine learning methods with model interpretability tools to identify key success factors for central bank digital currency (CBDC) projects. The support vector machine (SVM) method is used to build a classification model, GridSearchCV optimises the hyperparameters of the support vector model, and SHAP allows the importance of each factor in decision-making to be assessed. This approach ensures high prediction accuracy and understanding of the role of each factor in the implementation of a CBDC project, which is important for understanding this process and achieving the research objective.

3. RESULTS

In accordance with the previously established methodology and objectives of the study, the selection of optimal hyperparameters and the construction of a classification model using the support vector method were carried out to identify factors influencing the implementation of central bank digital currency (CBDC) projects.

As part of the preparation of data for further analysis and modelling, descriptive statistics of variables were assessed, including checking for missing values, the results of which are presented in Table 2. To improve data quality and avoid distortion of the analysis, missing values for most variables were replaced with the mean value for quantitative variables. The exceptions are variables x_1 and x_2 (variables related to public interest): for these, all missing values were filled with 0. This replacement is based on the assumption that if data on the public interest indicator for this project are missing, then the value of the corresponding indicator is low or zero. This approach ensured the correctness of subsequent modeling stages.

http://dx.doi.org/10.21511/bbs.21(1).2026.13

Table 2. Descriptive statistics of the variables in the dataset

Variable	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis	Number of null values
x_1	25.4	37.8	1.0	161.0	2.5	5.6	39
x_2	24.0	19.1	2.0	94.0	1.4	1.1	6
x_3	2020.3	3.1	1992.0	2024.0	-5.1	43.7	0
x_4	1.3	1.1	0.0	6.0	1.8	3.2	12
x_5	59.9	42.3	1.0	151.0	0.5	-0.9	10
x_6	8.3	19.2	0.1	221.3	9.4	102.6	11
x_7	1.7E+12	4.9E+12	2.8E+08	2.8E+13	4.5	19.8	6
x_8	1.7	1.2	1.0	7.0	2.0	3.7	0
x_9	1.1	1.6	0.0	5.0	1.4	0.9	0
x_{10}	1.6	0.9	0.0	3.0	0.6	-1.1	0
y	0.2	0.4	0.0	1.0	1.9	1.5	0

Based on the asymmetry and excess indicators (Table 2), it can be seen that the distribution of most variables is not normal.

The verified model parameter grid included the values shown in Figure 1, as they allow for the verification of various scenarios, from relatively simple (linear kernel, small *C*, and gamma values) to relatively complex (non-linear kernels, large parameter values) models. Accuracy was chosen as the metric for selecting the best parameters.

It should be noted that in the initial sample, the dependent variable showed a significant imbalance between classes: Figure 1 shows that 83.85% of all CBDC projects were in the early stages of development or had been cancelled, i.e., they had Class 0. The use of such unbalanced data could lead to inaccuracies in the model with the less represented class (in this case, Class 1 – CBDC projects in the final stages of implementation). To solve this problem, the ADASYN (Adaptive Synthetic Sampling) method from the imblearn library of the imblearn.over_sampling module for Python was used. This method is an extension of the SMOTE (Synthetic Minority Over-sampling Technique) method and allows the creation of new observations in those areas of feature space where samples of the less common class are most difficult to classify (He et al., 2008). As a result of using the ADASYN method, a balanced dataset of 270 observations was created (Figure 2), 50% of which belong to Class 1 (developed CBDC projects) and 50% to Class 0 (CBDC projects in the early stages of development or cancelled).

To further evaluate the model's performance on new data, the prepared dataset was divided into training and test samples in a ratio of 85% to 15%, corresponding to 229 observations in the training sample and 41 observations in the test sample. A relatively high percentage of observations for the test sample was chosen for an objective evaluation of the model for overfitting under conditions of a relatively small data set (270 observations in total). This ratio provides an adequate amount of data for training the model and also allows for an objective assessment of its accuracy on unknown data.

Thus, the implementation of the described stages (data collection and analysis, processing of missing values, scaling and balancing of the set, as well as data distribution and test and training samples) ensures the preparation of a high-quality data set for modelling using the support vector method, aimed at identifying the key factors for the implementation of CBDC projects.

```
param_grid = {
    'C': [0.01, 0.1, 0.5, 1, 5, 10],
    'gamma': [0.01, 0.1, 0.5, 1, 5, 10, 'scale'],
    'kernel': ['linear', 'poly', 'rbf', 'sigmoid']
}
```

Figure 1. Parameter grid for selecting optimal hyperparameters of the Support Vector Classifier model

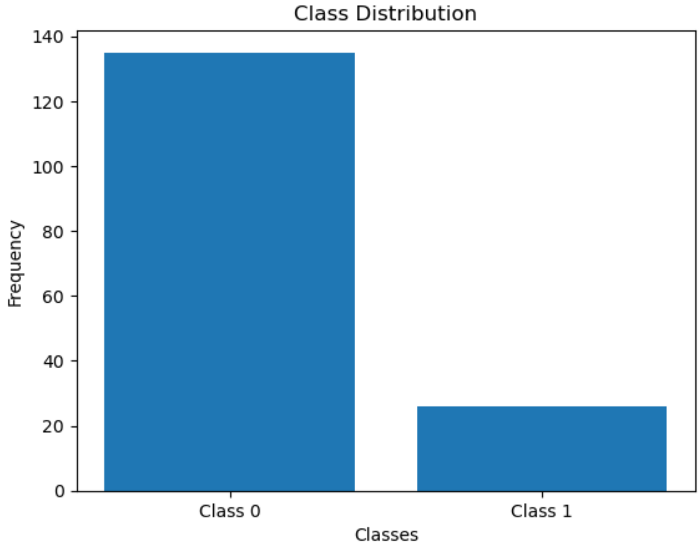

Figure 2. Distribution of values of the dependent variable (y) by classes before balancing

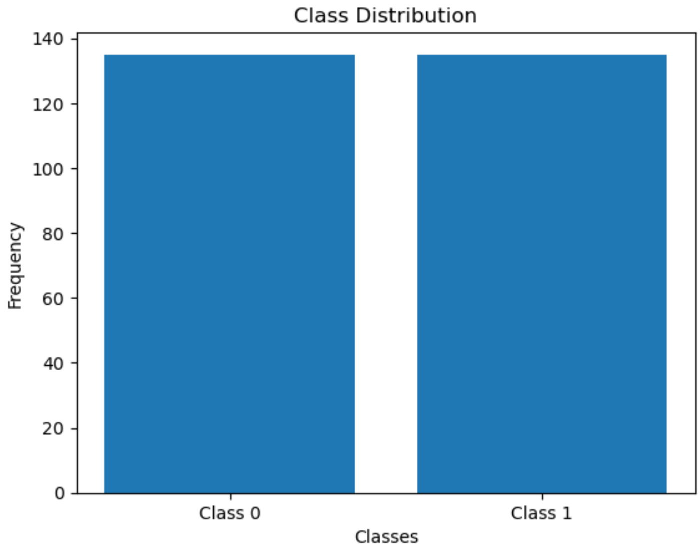

Figure 3. Distribution of values of the dependent variable (y) by classes after balancing by the ADASYN method

GridSearchCV goes through all possible combinations of parameters from a given grid (in this case, 6 × 7 × 4 = 168 combinations), performs 5-fold cross-validation for each combination, and selects the combination with the highest average accuracy. This procedure ensures a stable model evaluation and prevents overfitting, since the final evaluation is based on the classification results on data that was not used to train the model during each cross-validation iteration.

As a result of hyperparameter optimization using GridSearchCV, the most optimal support vector machine model for predicting the implementation status of central bank digital currency projects was selected using a standard hyperparameter grid. GridSearchCV results showed that the optimal parameters for the support vector machine model include:

- radial basis kernel: allows the model to detect nonlinear dependencies between project implementation factors, which is to be expected, since the implementation of CBDC projects depends on the complex interaction of economic, technological, and institutional factors, which would be difficult to describe using linear dependencies;

http://dx.doi.org/10.21511/bbs.21(1).2026.13

- regularization parameter C equal to 10: indicates a strict approach to classification; since the dataset contains a limited number of observations (270 after balancing), a high value of C can make the model less generalized, but it also increases the risk of overfitting;
- gamma parameter equal to 10: a relatively high value of the parameter means that the model focuses on local data patterns, and each observation only affects points close to it in the feature space, which is important for distinguishing between projects with similar but not identical characteristics.

The optimal support vector machine model achieved a moderately high classification accuracy of 93.90% during cross-validation, indicating relatively high effectiveness in predicting and selecting key factors for CBDC implementation. This result can be improved by taking into account additional variables that would indicate more unique local features of different CBDC projects (e.g., project goals, central bank activity, selected technological solutions, etc.).

To check the model for overfitting, it was tested on a test sample (Table 3). Based on the model classification accuracy indicators, we can see that the overall accuracy of the model is 0.88. This means that the model correctly classifies 88% of the observations in the test sample. This indicator is quite high and close to the results of the model on the training sample. In addition, the level of prediction accuracy is close in value for both classes, i.e., the model classifies both more developed CBDC projects (Class 1) and less developed or cancelled CBDCs (Class 0) equally well. Thus, we conclude that although the obtained model is quite well-fitted to the training data, it can also be used to predict the implementation status of CBDC projects on new observations.

A detailed analysis of classification metrics for individual classes (Figure 4) provides a deeper understanding of the model's effectiveness. For example, for Class 0 (early-stage or cancelled projects), the precision value is 1.00, meaning that all observations marked as undeveloped CBDC projects were indeed undeveloped, while the recall of 0.75 indicates that 25% of undeveloped CBDC projects were misclassified. For Class 1 (implemented or pilot CBDC projects), recall is 1.00, indicating the model's ability to correctly identify all observations in this class, while precision of 0.81 means that 19% of observations that were marked as implemented CBDC projects actually turned out not to be. High $F1$-score values for both classes (0.86 and 0.89, respectively), as well as macro-average and weighted average values, confirm the balanced and stable quality of the model.

The support vector method does not provide direct weight coefficients for assessing the impact of individual features on the classification result, so the SHAP method was used to determine the most influential features. The final visualization graph of this method for text sample observations is shown in Figure 4. The final SHAP graph combines information about the importance of features and their impact on the model (Molnar, 2024). The features on the graph are sorted by their importance for the classification result of the observation. According to this principle, the most influential features for the implementation of CBDC projects are x_{10} (direction of CBDC use), x_6 (inflation in the country of origin of the project), x_5 (the project's country of origin rating on the cryptocurrency acceptance index), x_1 (the number of scientific papers related to CBDC from the project's country of origin), and x_9 (the number of international CBDC projects in which the project's country of origin participates).

The color change of observations on the final SHAP plot illustrates the value of the corresponding feature, ranging from low (blue) to high (pink). The

Table 3. Classification results of the support vector machine model for the test dataset

Outcome Class	precision	recall	fl-score	support
0	1.00	0.75	0.86	20
1	0.81	1.00	0.89	21
accuracy	–	–	0.88	41
macro avg	0.90	0.88	0.88	41
weighted avg	0.90	0.88	0.88	41

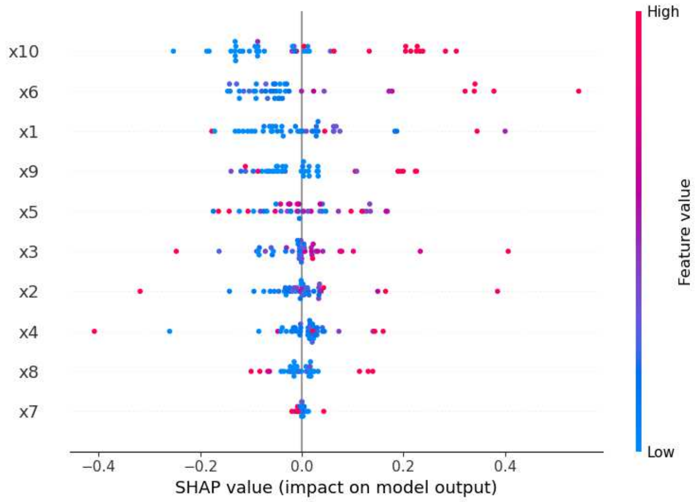

Figure 4. SHAP Summary Plot for the support vector model (SVM)

quantitative assessment of values as 'high', 'medium', and 'low' is based on a normalized scale [0, 1] after applying the MinMaxScaler method. Since all input data has been reduced to a single range, 'low values' correspond to values close to 0 (the left boundary of the distribution of a particular feature), 'high' values correspond to values close to 1 (the right boundary of the distribution), and average values correspond to the median values in the sample. The horizontal axis reflects SHAP values, where positive values increase the probability of classifying a project as implemented (class 1), and negative values decrease this probability. Thus, the result obtained indicates that:

- High values of variable x_{10} (direction of CBDC use) have a positive effect on the probability of classifying an observation as a realized CBDC project (Class 1), i.e., mixed-use or wholesale CBDC projects have the highest chances of being realized, while retail projects are more likely to be in the early stages of implementation.
- High values of variable x_6 (inflation in the country of origin of the project) have a positive effect on the probability of classifying the observation as a realized CBDC project (Class 1), while the lowest values of variable x_6, on the contrary, reduce the probability of the project's successful implementation.
- The influence of feature x_5 (the rating of the project's country of origin according to the cryptocurrency acceptance index) on the classification result is significant but less linear and obvious, and requires further study. However, it can be noted that low values of the feature (blue colour) tend to lead the model to conclude that the CBDC project is not feasible (negative SHAP values), i.e., countries with low levels of cryptocurrency acceptance are less likely to implement CBDC projects due to society's unwillingness to accept and use digital currencies in general.
- A medium or high value of x_1 (number of scientific papers related to CBDC from the country of origin of the CBDC project) increases the chances of classifying the CBDC project as implemented (class 1), i.e., CBDC projects that attract the interest of the scientific community have a greater chance of being implemented.
- A medium or high value of x_9 (the number of international CBDC projects in which the country of origin of the CBDC project participates) also increases the chances of a CBDC project being classified as implemented (Class 1), i.e., the more involved a country is in international initiatives related to sovereign digital currencies, the greater its chances of implementing its own CBDC projects.

Thus, in the course of the study, a support vector machine model was constructed with a classification accuracy of 90.76%, confirmed by the results of cross-validation of the training sample and classification of the test sample observations. The use

http://dx.doi.org/10.21511/bbs.21(1).2026.13

of the SHAP method made it possible to identify the key factors influencing the implementation of CBDC projects, including the direction of CBDC use, inflation, and the level of interest of scientists in digital currencies in the country of origin of the project, participation in international initiatives related to digital currencies, and the level of acceptance of cryptocurrencies. The results provide a new understanding of the importance of individual factors in the context of successful CBDC implementation, which can serve as a basis for further research and practical recommendations for central banks.

4. DISCUSSION

The empirical results demonstrate that the SVM-SHAP framework provides strong predictive discrimination between advanced and early cancelled-CBDC projects, but the main contribution lies not in accuracy alone, but in how the ranked drivers compare with existing research. While prior studies have identified numerous potential determinants of CBDC progress, most remain descriptive or thematic (Koparan, 2025; Shafranova et al., 2024). The present findings move beyond descriptive heterogeneity by empirically ranking the relative importance of these drivers within a unified global sample.

The most important predictor of advancement is use-case direction (x_{10}). Existing literature emphasizes that CBDCs must fit into national digital ecosystems and banking structures (Abbasova et al., 2025; Anton & Afloarei Nucu, 2024), and that institutional alignment is crucial for scaling digital finance (Waliszewski et al., 2024; Hedau, 2025). However, prior research generally treats retail and wholesale models as design alternatives rather than empirically differentiated trajectories. The findings extend this literature by showing that wholesale and mixed (retail-wholesale) orientations are systematically associated with higher advancement probability. This suggests that the ecosystem-compatibility argument proposed in earlier studies has measurable predictive consequences. In contrast to more technology-centric interpretations (Polishchuk, 2023a), the evidence indicates that strategic positioning within existing intermediation channels matters more than technological readiness alone. Thus, the results empirically validate governance-oriented interpretations of digital infrastructure implementation (Androniceanu & Streimikiene, 2025; Bartuseviciene & Butkus, 2024) and show that use-case choice is not merely technical, but structurally decisive.

The second most influential factor, inflation (x6), confirms macro-financial arguments that monetary instability increases the salience of CBDC development (Tanriverdi et al., 2024; Jabiyev et al., 2025). Previous research has suggested that currency turbulence and intervention pressures may motivate digital monetary innovation (Yoshimori, 2025), yet empirical cross-country testing has been limited. The current results provide quantitative support for these claims: higher inflation is associated with a greater likelihood of advancement. This conclusion complements IMF and BIS narratives that CBDCs gain urgency during monetary stress, but it also adds nuance. Inflation does not appear as an isolated driver; rather, it interacts with institutional and ecosystem readiness. This partially aligns with the argument that digitalization under weak institutional conditions may create stability risks (Bozhenko et al., 2024), reinforcing that macro pressure alone is insufficient without governance capacity (Kuzior et al., 2022; Kuzior et al., 2025).

The role of crypto adoption ranking (x5) offers a more differentiated contribution relative to previous studies. Earlier research presents two competing interpretations: crypto familiarity may either support CBDC readiness (Islam et al., 2024) or represent competitive pressure that complicates state-led initiatives (Gherghina & Constantinescu, 2024; Niftiyev & Kheyirkhabarli, 2024). The SHAP results suggest a conditional and partly non-linear relationship. Countries with very low crypto adoption are less likely to advance CBDC projects, supporting the "digital familiarity" hypothesis. However, high crypto penetration does not linearly guarantee advancement, which resonates with the competitive narrative (Maghyereh et al., 2025; Huang & Hsu, 2025). This reconciles prior debates by indicating that crypto ecosystems simultaneously act as readiness enablers and strategic competitors. Thus, CBDC adoption appears most likely when central banks respond strategically to the diffusion of digital assets rather than ignoring it (Koziuk et al., 2025; Wieczorek & Postrzednik-Lotko, 2025).

The significance of CBDC-related research output (x1) and international participation (x9) aligns with the digital-transformation literature's emphasis on institutional learning and knowledge diffusion (Pakhnenko et al., 2025; Dečman et al., 2025). Earlier studies highlight governance maturity and ethical readiness as latent drivers of banking transformation (Sitnicka et al., 2025), but rarely operationalize them quantitatively. The present model demonstrates that knowledge production and cross-border cooperation are among the top-ranked predictors of advancement. This finding empirically substantiates claims that analytical capacity and regulatory cooperation enhance the implementation of digital finance (Lyeonov et al., 2024a; Lyeonov et al., 2024b; Lyeonov et al., 2025). It also aligns with research linking cybersecurity, AML efficiency, and digital convergence to institutional readiness (Kuzior et al., 2022; Yarovenko et al., 2024b; Zolkover & Ovcharenko, 2024). Compared with prior thematic arguments, the contribution here lies in demonstrating that these "soft capacity" variables rank alongside macroeconomic factors in predictive importance.

Interestingly, some variables often highlighted in the literature (e.g., GDP size or telecommunications infrastructure) did not emerge among the strongest SHAP-ranked predictors. This contrasts with digital divide narratives that suggest infrastructure maturity is a primary constraint (Dečman et al., 2025). The results imply that while infrastructure is necessary, it may not be the decisive differentiator once a minimum threshold is reached. Instead, strategic design and ecosystem alignment appear more influential in distinguishing advanced from early projects.

The model achieves perfect recall for advanced projects but misclassifies a subset of early-stage cases. This pattern supports the path-dependency argument discussed in digital transformation research (Conley, 2025; Sidii, 2025). Some early projects share structural characteristics with advanced movers and may progress under favorable institutional or political shifts. This interpretation aligns with evidence on shock-induced acceleration in digital sectors (Prokopenko et al., 2022; Rybalchenko et al., 2022).

The findings should be interpreted in light of several limitations. The analysis is cross-sectional (December 2024) and therefore cannot establish temporal causality. The binary dependent variable compresses heterogeneous project stages, potentially masking maturity gradients. Mean imputation and zero-filling may introduce measurement bias. Synthetic balancing through ADASYN improves minority-class learning but alters the empirical distribution. Finally, SHAP values reflect model-based associations rather than causal effects; the identified drivers should therefore be interpreted as predictive correlates within the specified modelling framework.

CONCLUSION

The aim of this study is to identify and explain the key structural, macroeconomic, technological, and ecosystem-related factors that differentiate CBDC initiatives advancing to pilot or implementation stages from those remaining in early research or being discontinued across countries worldwide.

The model shows solid predictive capacity, indicating that advancement of CBDC initiatives is not random but systematically associated with identifiable structural and strategic conditions. In particular, project use-case orientation, inflation, crypto adoption environment, domestic research engagement, and international participation emerge as the most relevant predictors. Wholesale or mixed-use designs, stronger macroeconomic pressure, greater scientific activity, and deeper international involvement are generally associated with a higher likelihood of reaching pilot or implementation stages, while low crypto ecosystem readiness is linked to slower progress.

Based on these findings, policy recommendations should focus on strategically aligning CBDC design choices, macroeconomic positioning, institutional capacity-building, and ecosystem readiness to enhance the likelihood of successful project advancement. First, central banks should treat use-case design as a strategic lever: the results imply that projects framed as mixed retail–wholesale

http://dx.doi.org/10.21511/bbs.21(1).2026.13

or wholesale-focused are more likely to mature, so early roadmaps should explicitly prioritize high-value institutional use-cases (e.g., interbank settlement, securities settlement, cross-border corridors) alongside any retail ambitions, rather than starting with a "retail-only" scope by default. Second, because inflation is a key predictor of advancement, CBDC programs should be embedded in a broader macroeconomic and payments-resilience narrative (e.g., improving payment efficiency, reducing cash-management costs, strengthening monetary transmission or settlement reliability), while simultaneously designing safeguards that prevent the project from being perceived as a short-term anti-inflation "fix" (clear limits, privacy-by-design, and phased rollouts). Third, the prominence of knowledge production and international cooperation suggests that "capacity to learn" is not peripheral but central to project success. Central banks can operationalize this by funding research and pilots with universities and fintechs, publishing technical findings (to build credibility and implementation know-how), and joining multi-country experimentation networks to accelerate standards alignment and reduce implementation risk. Finally, the role of crypto adoption readiness indicates that where societal familiarity with digital assets and related services is low, CBDC rollouts may face higher adoption and legitimacy barriers; therefore, policymakers should pair CBDC work with broader digital financial literacy, clear regulatory frameworks for digital payments/innovation, and user-centered communication strategies that translate technical goals into public value (security, convenience, cost, and trust).

AUTHOR CONTRIBUTIONS

Conceptualization: Zhanat Khishauyeva, Diana Sitenko, Vitaliia Koibichuk, Arsen Petrosyan, Gaukhar Kodasheva, Ekaterina Dmitrieva, Kseniia Mohylna.
Data curation: Vitaliia Koibichuk, Kseniia Mohylna.
Formal analysis: Vitaliia Koibichuk, Ekaterina Dmitrieva, Kseniia Mohylna.
Funding acquisition: Zhanat Khishauyeva.
Investigation: Vitaliia Koibichuk, Kseniia Mohylna.
Methodology: Vitaliia Koibichuk, Kseniia Mohylna.
Project administration: Vitaliia Koibichuk.
Resources: Arsen Petrosyan.
Software: Vitaliia Koibichuk, Gaukhar Kodasheva, Kseniia Mohylna.
Supervision: Vitaliia Koibichuk, Kseniia Mohylna.
Validation: Vitaliia Koibichuk, Ekaterina Dmitrieva, Kseniia Mohylna.
Visualization: Diana Sitenko, Vitaliia Koibichuk, Kseniia Mohylna.
Writing – original draft: Zhanat Khishauyeva, Diana Sitenko, Vitaliia Koibichuk, Arsen Petrosyan, Gaukhar Kodasheva, Kseniia Mohylna.
Writing – reviewing & editing: Zhanat Khishauyeva, Diana Sitenko, Vitaliia Koibichuk, Arsen Petrosyan, Gaukhar Kodasheva, Ekaterina Dmitrieva, Kseniia Mohylna.

REFERENCES

1. Abbasova, S., Vasylieva, T., Aliyeva, M., Gubadova, A., Ashurbayli-Huseynova, N., & Kasumova, L. (2025). Factors linking upper-middle- and high-income countries in terms of banking ecosystem digitalization: Cluster analysis. *Banks and Bank Systems, 20*(3), 75-90. https://doi.org/10.21511/bbs.20(3).2025.06
2. Al-Smadi, M. O. (2025). Insurance sector readiness for digital transformation: Empirical evidence from Jordan. *Insurance Markets and Companies, 16*(1), 33-41. http://dx.doi.org/10.21511/ins.16(1).2025.03
3. Androniceanu, A., & Streimikiene, D. (2025). Reinventing public managers in the digital age: competencies and innovative governance models across the European Union. *Administratie si Management Public, 45,* 69-90. https://doi.org/10.24818/amp/2025.45-04
4. Anton, S., & Afloarei Nucu, A. E. (2024). The impact of digital finance and financial inclusion on banking stability: International evidence. *Oeconomia Copernicana, 15*(2), 563-593. https://doi.org/10.24136/oc.3046
5. Ashurbayli-Huseynova, N., & Garmidarova, Y. (2025). Bank capital management in emerging and frontier markets: Bibliometric analysis. *Banks and Bank Systems, 20*(1), 304-322. https://doi.org/10.21511/bbs.20(1).2025.25

6. Banerjee, S. (2025). Decoding currency dynamics: A multiscale machine learning approach integrating economic indicators, ESG, and investor sentiment. *Investment Management and Financial Innovations, 22*(3), 27-48. https://doi.org/10.21511/imfi.22(3).2025.03

7. Bartuseviciene, I., & Butkus, M. (2024). The effect of digital governance to stimulate the antifragile capabilities of public sector organizations. *Economics and Sociology, 17*(3), 41-61. http://dx.doi.org/10.14254/2071-789X.2024/17-3/3

8. Bozhenko, V., Boyko, A., Vondráček, M., & Karácsony, P. (2024). Shadow economy and financial stability from the perspective of finance digitalization. *Journal of International Studies, 17*(2), 191-205. http://dx.doi.org/10.14254/2071-8330.2024/17-2/10

9. CBDC Tracker. (2024). *Today's Central Bank Digital Currencies Status*. Retrieved from https://cbdctracker.org/

10. Chainalysis. (2024). *The 2024 geography of crypto report* (Chainalysis report). Retrieved from https://www.chainalysis.com/wp-content/uploads/2024/10/the-2024-geography-of-crypto-report-release.pdf

11. Conley, L. (2025). Bridging Analog and Digital: A Case Study on Pandemic Accelerated Digital Disruption in Healthcare Retail. *Health Economics and Management Review, 6*(4), 11-27. https://doi.org/10.61093/hem.2025.4-02

12. Dečman, M., Klun, M., & Stare, J. (2025). A latent profile analysis of DigComp dimensions and the alignment with EU digital goals: a case of Slovenia. *Administratie si Management Public, 45*, 46-68. https://doi.org/10.24818/amp/2025.45-03

13. Demmou, L., & Sagot, Q. (2021). *Central Bank Digital Currencies and payments: A review of domestic and international implications* (OECD Economics Department Working Papers No. 1655). Paris: OECD Publishing. https://doi.org/10.1787/f06c0d89-en.

14. Dunbar, E. (2023, 17 February). *Understanding Shapley Explanatory Values (SHAP)*. LinkedIn. Retrieved from https://www.linkedin.com/pulse/understanding-shapley-explanatory-values-shap-evan-dunbar/

15. Eletter, S.F. (2024). The use of blockchain in the insurance industry: A bibliometric analysis. *Insurance Markets and Companies, 15*(1), 12-29. http://dx.doi.org/10.21511/ins.15(1).2024.02

16. Elsevier. (n.d.). *Scopus: A comprehensive abstract and citation database for impact makersю* . https://www.elsevier.com/products/scopus

17. European Central Bank (ECB). (2025). *Progress on the preparation phase of a digital euro*. Frankfurt am Main: European Central Bank. https://doi.org/10.2866/4341358

18. Gherghina, Ș.-C., & Constantinescu, C.-A. (2024). Examining herding behavior in the cryptocurrency market. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 19*(3), 749-792. https://doi.org/10.24136/eq.3057

19. Google Trends. (2024). *Google Trends*. https://trends.google.com/

20. He, H., Bai, Y., García, E. A., & Li, S. (2008). ADASYN: Adaptive synthetic sampling approach for imbalanced learning. *2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence)* (p. 1322-1328). IEEE. https://doi.org/10.1109/IJCNN.2008.4633969

21. Hedau, A. (2025). Socio-Economic Challenges of Digital Banking Adoption: The Impact of Perceived Usefulness, Ease of Use, and Self-Efficacy. *SocioEconomic Challenges, 9*(3), 133-146. https://doi.org/10.61093/sec.9(3).133-146.2025

22. Huang, C. C., & Hsu, C. C. (2025). Connectedness between DeFi assets and TradFi sectors in emerging Asian markets. *Investment Management and Financial Innovations, 22*(4), 83-94. https://doi.org/10.21511/imfi.22(4).2025.07

23. Illes, A., Kosse, A., & Wierts, P. (2025, August). *Advancing in tandem: Results of the 2024 BIS survey on central bank digital currencies and crypto* (BIS Papers No. 159). Bank for International Settlements. Retrieved from https://www.bis.org/publ/bppdf/bispap159.pdf

24. International Monetary Fund (IMF). (2024). Central bank digital currency – Progress and further considerations (Staff report). Washington, D.C.: International Monetary Fund. Retrieved from https://www.imf.org/-/media/files/publications/pp/2024/english/ppea2024052.pdf

25. Islam, K. M.A., Omeish, F., Islam, S., Sarea, A. M. Y., & Abdrabbo, T. (2024). Exploring individuals' purchase willingness for cryptocurrency in an emerging context. *Innovative Marketing, 20*(2), 230-239. https://doi.org/10.21511/im.20(2).2024.19

26. Jabiyev, F., Mukhtarov, S., Gasim, N., & Gafarli, G. (2025). Assessing the macroeconomic impact of quantitative easing: Successes and shortfalls. *Economics and Sociology, 18*(3), 137-159. https://doi.org/10.14254/2071-789X.2025/18-3/8

27. Jumaiyah, Andayani, W., Rosidi, R., & Purwanti, L. (2025). Digital transformation in village financial management: A bibliometric analysis of research evolution and contemporary challenges. *Public and Municipal Finance, 14*(2), 15-28. https://doi.org/10.21511/pmf.14(2).2025.02

28. Klochan, I., & Filipov, D. (2023). Design of assessment and forecasting of a country's financial security in a change management conditions. *Smart Economy, Entrepreneurship and Security, 1*(1), 31-42. https://doi.org/10.60022/sis.1.(01).3

29. Koonprasert, T., Tunyathon, T., Kanada, S., Tsuda, N., & Reshidi, E. (2024). *Central bank digital currency adoption: Inclusive strategies for intermediaries and users* (IMF Fintech Note No. 2024/005). Washington, DC.: International Monetary Fund. Retrieved from

http://dx.doi.org/10.21511/bbs.21(1).2026.13

https://www.imf.org/-/media/files/publications/ftn063/2024/english/ftnea2024005.pdf

30. Koparan, A. (2025). Central Bank Digital Currencies: A review of global trends in adoption, financial inclusion, and the role of country characteristics. *Investment Management and Financial Innovations, 22*(1), 107-121. http://dx.doi.org/10.21511/imfi.22(1).2025.09

31. Koziuk, V., Ivashuk, Y., & Haida, Y. (2025). Privacy Preferences and Trust in Central Banks: Heterogeneity in the Case of CBDC. *Financial and Credit Activity Problems of Theory and Practice, 3*(62), 11-25. https://doi.org/10.55643/fcaptp.3.62.2025.4734

32. Kuzior, A., Vasylieva, T., Smutka, L., & Haj Ammar, O. (2025). Toward tailored AML/CFT strategies: Clustering countries by FATF compliance and effectiveness. *Journal of International Studies, 18*(2), 229-254. https://doi.org/10.14254/2071-8330.2025/18-2/13

33. Kuzior, A., Zakharkina, L., Kubaščikova, Z., Chentsov, V., & Lyeonov, S. (2023). Insurance Market Transparency Research Trends: A Bibliometric Analysis. *Insurance Markets and Companies, 14*(1), 136-152. https://doi.org/10.21511/ins.14(1).2023.12

34. Kuzior, A., Vasylieva, T., Kuzmenko, O., Koibichuk, V., & Brożek, P. (2022). Global Digital Convergence: Impact of Cybersecurity, Business Transparency, Economic Transformation, and AML Efficiency. *Journal of Open Innovation: Technology, Market, and Complexity, 8*(4), 195. https://doi.org/10.3390/joitmc8040195

35. Kuznetsov, A., Lutsenko, M., Kuznetsova, K., Martyniuk, O., Babenko, V., & Perevozova, I. (2019). Statistical testing of blockchain hash algorithms. In Fedushko, S., Gnatyuk, S., Peleshchyshyn, A., Hu, Z., Odarchenko, R., & Korobiichuk, I. (Eds.), *CEUR workshop proceedings: 2019 International Workshop on Conflict Management in Global Information Networks (CMiGIN 2019)*. CEUR-WS. Retrieved from https://ceur-ws.org/Vol-2588/paper7.pdf

36. Lyeonov, S., Draskovic, V., Kubaščikova, Z., & Fenyves, V. (2024a). Artificial intelligence and machine learning in combating illegal financial operations: Bibliometric analysis. *Human Technology, 20*(2), 325-360. https://doi.org/10.14254/1795-6889.2024.20-2.5

37. Lyeonov, S., Hrytsenko, L., Trojanek, R., & Popp, J. (2025). Who benefits from AI in money laundering in Europe: The organised criminals or the AML services? *Human Technology, 21*(1), 222-245. https://doi.org/10.14254/1795-6889.2025.21-1.11

38. Lyeonov, S., Tumpach, M., Loskorikh, G., Filatova, H., Reshetniak, Y., & Dinits, R. (2024b). New AML tools: analyzing Ethereum cryptocurrency transactions using a Bayesian classifier. *Financial and Credit Activity Problems of Theory and Practice*, *4*(57), 274-288. https://doi.org/10.55643/fcaptp.4.57.2024.4500

39. Maghyereh, A., Al-Shboul, M., & Awartani, B. (2025). Gold-backed cryptocurrencies in cryptocurrency portfolios: Evaluating their hedging capabilities and safe-haven characteristics during extreme market conditions. *Oeconomia Copernicana, 16*(1), 317-388. https://doi.org/10.24136/oc.3272

40. Máté, D., Raza, H., Ahmad, I., & Kovács, S. (2024). Next step for Bitcoin: Confluence of technical indicators and machine learning. *Journal of International Studies, 17*(3), 68-94. https://doi.org/10.14254/2071-8330.2023/17-3/4

41. Mercer-Bey, Y. (2025). Digital Transformation in Public Health and Safety: Integrating Drones, GIS, and Satellite Technology in Emergency Wildfire Response. *Health Economics and Management Review, 6*(3), 17-27. https://doi.org/10.61093/hem.2025.3-02

42. Molnar, C. (2024). *Interpretable machine learning: A guide for making black box models explainable* (2nd ed.). Lean Publishing. Retrieved from https://christophm.github.io/interpretable-ml-book/

43. Mouna, B., & Yassine, M. (2024). Business Leadership in E-Commerce in the USA: The Impact of Blockchain Technology. *Business Ethics and Leadership, 8*(1), 116-128. https://doi.org/10.61093/bel.8(1).116-128.2024

44. Niftiyev, I. & Kheyirkhabarli, M. (2024). The Impact of Covid-19 Pandemic on Cryptocurrency Adoption in Investments: a Bibliometric Study. *SocioEconomic Challenges, 8*(1), 154-169. https://doi.org/10.61093/sec.8(1).154-169.2024

45. Omeir, A. K., & Vasiliauskaite, D. (2025). Climate change challenges in central banking: A systematic review with bibliometric and content analysis. *Banks and Bank Systems, 20*(2), 206-222. https://doi.org/10.21511/bbs.20(2).2025.17

46. Pakhnenko, O., Yarovenko, H., Semenog, A., Mordan, Y., & Tarasenko, O. (2025). Uncovering patterns of digital transformation of European economies using self-organizing maps. *Problems and Perspectives in Management, 23*(3), 581-596. https://doi.org/10.21511/ppm.23(3).2025.42

47. Polishchuk, Y. (2023). Fintech future trends. In J. Lubacha, B. Mäihäniemi, & R. Wisła (Eds.), *The European digital economy: Drivers of digital transition and economic recovery* (pp. 204-220). Routledge. https://doi.org/10.4324/9781003450160-15

48. Pozovna, I., Duranowski, W., Pankiv, O., Kalenyuk, I., & Fomenko, S. (2025). Transformation of Stock Market Threats into Investment Opportunities: Modelling the Dependence of the Indian and Vietnamese Stock Markets on the US–China Trade War. *Financial Markets, Institutions and Risks, 9*(2), 90-111. https://doi.org/10.61093/fmir.9(2).90-111.2025

49. Prokopenko, O., Zholamanova, M., Mazurenko, V., Kozlianchenko, O., & Muravskyi, O. (2022). Improving customer relations in the banking sector of Ukraine through the development of prior-

ity digital banking products and services: Evidence from Poland. *Banks and Bank Systems, 17*(3), 12-26. https://doi.org/10.21511/bbs.17(3).2022.02

50. Reuters. (2025, December 19). *EU Council backs digital euro with both online and offline functionality*. Retrieved from https://www.reuters.com/business/finance/eu-council-backs-digital-euro-with-both-online-offline-functionality-2025-12-19/

51. Rybalchenko, S., Lukianykhina, O., Alamanova, C., Saienko, V., & Sunduk, T. (2022). Anti-crisis management of banking institutions: current problems and prospects for improvement. *Financial and Credit Activity-Problems of Theory and Practice, 5*(46), 29-39. https://doi.org/10.55643/fcaptp.5.46.2022.3907

52. Said, S. N. R., Arifuddin, Kusumawati, A., & Usman, A. (2025). Does the concept of value for money increase budget performance? *Public and Municipal Finance, 14*(1), 1-12. https://doi.org/10.21511/pmf.14(1).2025.01

53. Shafranova, K., Navolska, N., & Koldovskyi, A. (2024). Navigating the digital frontier: a comparative examination of Central Bank Digital Currency (CBDC) and the Quantum Financial System (QFS). *SocioEconomic Challenges, 8*(1), 90-111. https://doi.org/10.61093/sec.8(1).90-111.2024

54. Sidii, F. S. (2025). Transforming Health Service Delivery through Digital Innovation: Overcoming Socio-Ecological Barriers and Bridging the Digital Divide. *Health Economics and Management Review, 6*(2), 60-75. https://doi.org/10.61093/hem.2025.2-05

55. Sitnicka, S., Mursalov, M., Mammadov, H., Babaiev, D., & Zhou, Y. (2025). Ethics, Institutions, Infrastructure, and Governance in AI National-Level Readiness: A Hidden Driver of Banking Transformation. *Business Ethics and Leadership, 9*(3), 290-304. https://doi.org/10.61093/bel.9(3).290-304.2025

56. Soussou, K., & Hamrouni, R. (2025). Behavioral Insights of Business Leadership: Exploring Determinants of Intention and Adoption of Digital Financial Services. *Business Ethics and Leadership, 9*(4), 135-162. https://doi.org/10.61093/bel.9(4).135-162.2025

57. Tanriverdi, I., Jabiyev, F., Bilan, Y., Azizov, M., & Ibadov, E. (2024). The Relationship between Monetary Stability and Central Bank Independence: The Case of Azerbaijan. *Banks and Bank Systems, 19*(1), 74-85. https://doi.org/10.21511/bbs.19(1).2024.07

58. Tarasenko, I., Saienko, V., Kirizleyeva, A., Vozniakovska, K., Harashchenko, L., & Bodnar, O. (2022). Comparative characteristics of the banking sector in Eastern Europe. *International Journal of Computer Science and Network Security, 22*(1), 639-649. https://doi.org/10.22937/IJCSNS.2022.22.1.84

59. UN E-Government Knowledgebase (UNeGovKB). (2024). *Country Data*. Retrieved from https://publicadministration.un.org/egovkb/en-us/data-center

60. Waliszewski, K., Cichowicz, E., Gębski, Łukasz, Kliber, F., Kubiczek, J., Niedziółka, P., Solarz, M., & Warchlewska, A. (2024). Digital loans and buy now pay later from LendTech versus bank loans in the era of 'black swans': Complementarity in the area of consumer financing. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 19*(1), 241-278. https://doi.org/10.24136/eq.2982

61. Wieczorek, A., & Postrzednik-Lotko, K. (2025). Machine Learning Algorithms on Social Media: Privacy Risks, User Awareness and Security Implications. *Safety and Security Advances, 1*(1), 18-43. https://doi.org/10.61093/ssa.1(1).18-43.2025

62. World Bank. (n.d.). *Data bank world development indicators*. Retrieved from https://databank.worldbank.org/reports.aspx?source=2&series=FP.CPI.TOTL.ZG&country=WLD

63. Xuan, H. V. T., Huan, V. M., & Su, L. H. (2025). Mapping research trends in online shopping behavior during the fourth industrial revolution: A bibliometric analysis. *Innovative Marketing, 21*(4), 216-231. https://doi.org/10.21511/im.21(4).2025.16

64. Yarovenko, H., Kuzior, A., Norek, T., & Lopatka, A. (2024a). The future of artificial intelligence: Fear, hope or indifference? *Human Technology, 20*(3), 611-639. https://doi.org/10.14254/1795-6889.2024.20-3.10

65. Yarovenko, H., Pozovna, I., & Bylbas, R. (2024b). The Risk of Escalating Cyberattacks and Financial Fraud During Wartime: The Maturity of the County's Judicial System in Combating Cyber and Financial Crimes. *Financial Markets, Institutions and Risks, 8*(4), 126-147. https://doi.org/10.61093/fmir.8(4).126-147.2024

66. Yefimenko, A., Boronos, V., Serpeninova, Yu., & Koldovskyi, A. (2025). Innovative and Technological Determinants of Corruption Reduction: How do Knowledge and Technology Contribute to Public Integrity and Transparency? *Knowledge Economy and Lifelong Learning, 1*(1), 21-34. https://doi.org/10.61093/kell.1(1).21-34.2025

67. Yoshimori M. (2025). Asymetrix Currency Turbulence with US Dollar/Japanese Yen Carry Trade: Insights into Central Bank Interventions and Exchange-Rate Dynamics. *Financial Markets, Institutions and Risks, 9*(1), 74-98. https://doi.org/10.61093/fmir.9(1).74-98.2025

68. Zolkover, A., & Ovcharenko, P. (2024). Modelling a comprehensive assessment of the level of innovation security. *Smart Economy, Entrepreneurship and Security, 2*(1), 50-57. https://doi.org/10.60022/sis.2.(01).5

http://dx.doi.org/10.21511/bbs.21(1).2026.13

APPENDIX A. SAMPLE OF THE COUNTRIES IN ANALYSIS

Australia, Austria, Azerbaijan, Algeria, Argentina, Bahamas, Bangladesh, Bahrain, Belarus, Botswana, Brazil, Bhutan, Vanuatu, United Kingdom, Vietnam, Armenia, Haiti, Ghana, Guatemala, Hong Kong, Honduras, Georgia, Denmark, Dominican Republic, Ecuador, Eswatini, Ethiopia, Egypt, Yemen, Zambia, Zimbabwe, Israel, India, Indonesia, Iraq, Iceland, Spain, Jordan, Kazakhstan, Canada, Qatar, Kenya, Kyrgyzstan, China, Colombia, Costa Rica, Côte d'Ivoire, Kuwait, Curaçao, Laos, Lebanon, Luxembourg, Mauritius, Mauritania, Madagascar, Macao, Malawi, Malaysia, Maldives, Morocco, Mexico, Mongolia, Namibia, Nepal, Nigeria, New Zealand, Norway, United Arab Emirates, Oman, Pakistan, Palestine, Papua New Guinea, Paraguay, Peru, South Africa, South Korea, Poland, Republic of Palau, Rwanda, Saudi Arabia, Singapore, Solomon Islands, United States of America, Sudan, Thailand, Taiwan, Tanzania, Tonga, Trinidad and Tobago, Tunisia, Turkey, Uganda, Hungary, Ukraine, Uruguay, Fiji, Philippines, Finland, France, Czech Republic, Chile, Montenegro, Switzerland, Sweden, Sri Lanka, Jamaica, Japan.