J. Int. Financ. Markets Inst. Money 99 (2025) 102093

Contents lists available at ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

The crypto collapse chronicles: Decoding cryptocurrency exchange defaults

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ARTICLE INFO

JEL classification:
G10
G12
G14
G17

Keywords:
Cryptocurrency exchange
Defaults
Logit
Probit
Machine learning

ABSTRACT

This research explores the factors contributing to the failure of cryptocurrency exchanges by analyzing a sample of 845 exchanges. Using logit and probit models, it identifies key variables affecting cryptocurrency exchange defaults. The results show that cryptocurrency exchanges that are centralized, located in countries with high transparency indices, and offer fewer peer cryptocurrencies are more likely to default. Additionally, exchanges that impose high withdrawal fees and have no restrictions on clients from the United States are also positively associated with defaults. Moreover, the absence of referral schemes and having lower ratings each contributes marginally to defaults. Machine learning (ML) models including random forest, support vector machine, stacked ensemble confirm the robustness and high predictability of cryptocurrency exchange defaults.

1. Introduction

Several recent studies have delved into the complexity and continuous evolution of the cryptocurrency exchange market (for example, Makarov and Schoar, 2020; Dimpfl and Peter, 2021; Brauneis et al., 2022). Grone et al. (2021) investigate arbitrage opportunities across multiple cryptocurrency exchanges, revealing the potential profitability and risk in these markets. The ecosystem of cryptocurrency exchanges continually grapples with new challenges and dimensions, largely due to the remarkable expansion of decentralized finance (DeFi), Makridis et al. (2023). Consequently, the cryptocurrency market remains fraught with uncertainties. Caliskan (2022) suggests a new regulatory and taxation framework for cryptocurrencies in the United States (U.S.) considering them as data money and proposing a dynamic approach to exchange platform regulation. Several studies have examined the ongoing challenges in this fast-changing industry. For instance, Almeida and Gonçalves (2023) provide a systematic literature review on investor behavior in cryptocurrency markets, identifying herding behavior and market inefficiencies as key factors influencing investment decisions. Lansky (2020) analyzes the survival rates of over 2500 cryptocurrencies, showing that newer cryptocurrencies are more likely to fail and be delisted, whereas older ones have a higher survival probability. In their study Grobys and Sapkota (2020) reveal that within the four-year period between 2014 and 2018, approximately 60% of cryptocurrencies defaulted due to scams, hacks and business failures.

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[1] I gratefully acknowledge the research grants (grant numbers: 230391, 220290, and 210248) awarded by the Foundation for Economic Education (LIIKESIVISTYSRAHASTO), Finland. I extend my heartfelt gratitude to the editor, Professor Peter G. Szilagyi, and the four anonymous reviewers for their insightful and constructive comments, which significantly improved the quality of this paper. My thanks also go to Professor Emmanuel Mamatzkis and other participants of the 2nd International Workshop on Global Sustainable Innovation, University of Vaasa 2023, for their valuable input. I am particularly grateful to Associate Professor Sofia Johan for her feedback. I am also thankful to Associate Professor Gregory Gadzinski, Assistant Professor Sean Wilkoff, Post-Doctoral Researcher Stefan Scharnowski, and other attendees of the 6th Cryptocurrency Research Conference 2023, International University of Monaco, for their insightful comments.

https://doi.org/10.1016/j.intfin.2024.102093
Received 23 April 2024; Accepted 29 November 2024

Available online 4 December 2024

It is unsurprising that since the Mt. Gox collapse in 2014, roughly 60% of cryptocurrency exchanges have also faced defaults stemming from fraudulent activities, cyberattacks, government regulations, and various other reasons.[2] This study aims to predict the probability of cryptocurrency exchange default using open source data and to determine whether it is possible to differentiate between active and defaulted exchanges by implementing traditional statistical models alongside advanced machine learning algorithms.

Coinmarketcap.com, the leading price-tracking platform for crypto assets globally, ranks and assesses cryptocurrency exchanges based on parameters such as traffic, liquidity, trading volumes, and confidence in reported trading volumes. As of today (10.4.2023), 609 cryptocurrency exchanges have been included on this website. Unfortunately, only 237 of them have generated at least $1 worth of cryptocurrency trading in the preceding 24 hours.[3] Exchanges going bankrupt in traditional financial markets is a rare phenomenon. Even though these exchanges are centralized, in contrast, they do not hold their clients' funds in custody as in the centralized cryptocurrency exchanges. Therefore, bankruptcies of exchanges are rare occurrences in traditional financial markets, as they are highly regulated and have stringent risk management procedures in place to prevent such events from happening.

Many high-profile cryptocurrency exchange failures have left a mark on this ever-evolving industry. BTC-E was forced to cease operations in 2017 due to allegations of money laundering by U.S. authorities, while BTC-China was shut down in the same year in response to China's crackdown on cryptocurrencies. Canadian crypto exchange QuadrigaCX filed for bankruptcy in 2019 following the death of its Chief Executive Officer (CEO), which rendered $190 million in cryptocurrency inaccessible as he was the sole holder of the private keys to digital wallets. In 2021, Thodex, a major Turkish cryptocurrency exchange, froze when its founder CEO fled with all funds. Most recently, in 2022, FTX, the largest U.S.-based cryptocurrency exchange, collapsed with an $8 billion shortfall in its balance sheet, with allegations against the CEO playing a significant role in the default.[4] Conlon et al. (2023) discuss the collapse of the FTX exchange, emphasizing the ethical and regulatory flaws that contributed to its downfall and the broader implications for the cryptocurrency industry. Numerous news outlets have widely reported these incidents, while some research studies have also examined the impact of such failures on individual exchanges (for example, Kokorin et al., 2020; Fu et al., 2022; Jalan and Matkovskyy, 2023; Akyildirim et al., 2023). Moreover, it is worth noting that in addition to the high-profile exchange collapses, a plethora of lesser-known cryptocurrency exchanges are frequently defaulting or disappearing, resulting in significant societal impact.

Constructing a bankruptcy prediction model in the conventional financial market, either through the utilization of classical statistical techniques or advanced machine learning models, is a formidable task due to the disparate distribution between solvent and insolvent firms. As indicated by Garcia (2022), an imbalanced dataset denotes a scenario where the class of interest (i.e., the minority or positive case) is significantly smaller than other classes (i.e., the majority or negative case). This class imbalance can impede the effectiveness of classification algorithms, particularly when data is severely skewed towards one class. In this regard, Beaver et al. (2011), document that typically less than 1% of NYSE-AMEX firms and slightly more than 1% of NASDAQ firms go bankrupt in a given year. Given the low bankruptcy results, bankruptcy datasets are generally severely imbalanced, whereby bankrupt firms typically represent 1% or less of the observations thus making it difficult to extract a signal, increasing the difficulty of understanding the effect of variables on the dependent variable. The most widely used approach to correct class imbalance is data preprocessing which includes resampling such as over and under-sampling to alter the class distribution of the training data by resampling the data space. Resampling-based techniques avoid modification of the learning algorithm by decreasing the effect of the imbalance. Therefore, they are independent of the classifier and are usually more versatile, Galar et al. (2011). Among the data preprocessing techniques used, the most widely used class balancing technique is the synthetic minority oversampling technique (SOMTE); Fernández et al. (2018) and Garcia (2022).

The landscape of the new blockchain-based digital financial market differs significantly from the traditional financial market. This is due to the frequent defaults of cryptocurrencies (Grobys and Sapkota, 2020) and cryptocurrency exchanges, resulting in a nearly equal balance between default and non-default datasets. Hence, there is no need to generate synthetic data, as the rate at which cryptocurrency exchanges disappear or go into default is similar to those that remain operational.

A limited number of previous studies have investigated the factors influencing cryptocurrency exchange survival, employing various statistical and machine learning techniques. For instance, Fantazzini and Calabrese (2021) analyze data from 144 exchanges between 2018 and 2021, identifying key factors such as cybersecurity grades, public developer teams, exchange age, and the number of traded cryptocurrencies as significant predictors of closure. Their results are consistent across different models and datasets. Similarly, Milunovich and Lee (2022) examine 238 exchanges using machine learning to predict market viability, identifying exchange lifetime, transaction volume, and cybersecurity measures as critical determinants of exchange survival. Both studies demonstrate the efficacy of machine learning in forecasting exchange outcomes. Nevertheless, our study addresses existing research gaps by including additional factors not previously examined. These factors include the fee structure of the exchange (for example, maker, taker, and withdrawal fees), territorial restrictions (such as whether U.S. clients are allowed), the centralized or decentralized nature of the exchange, the presence of an affiliation program, the transparency index of the country where the exchange is registered as well as the ratings and certification. Our analysis also encompasses more recent and a larger sample of 845 cryptocurrency exchanges worldwide until February 2023. Although Mukherjee and Moore (2022) revisit the research on cryptocurrency exchange closures by analyzing 822 exchanges, incorporating factors such as U.S. customer access and maker fees, their analysis is limited to a logistic regression model with only a few variables. In contrast, our study takes into account fourteen distinct factors, offering a more comprehensive approach.

[2] See more at: https://cryptowisser.com/.

[3] See more at: https://coinmarketcap.com/rankings/exchanges/.

[4] See more at: https://www.entrepreneur.com/business-news/.

This article makes significant contributions to financial research, particularly in advancing literature, data frameworks, methodologies, and practical applications, with a focus on predicting, understanding, and mitigating risks in blockchain-based digital financial markets, specifically cryptocurrency exchanges and their risk of defaults. Firstly (*i*), this study contributes to address this gap by presenting a model that can aid in the risk assessment of cryptocurrency exchanges. While it utilizes traditional statistical models like logit and probit, it also examines the use of machine learning techniques such as random forest, support vector machine (SVM), gradient boosting machine (GBM), and stacked ensemble model (SEM) in predicting cryptocurrency exchange defaults. Secondly (*ii*), it also fills the gap in the literature on credit risk and the ongoing debate on the superiority of machine learning over conventional statistical techniques (for example, Galindo and Tamayo, 2000; Chatzis et al., 2018; Khedr et al., 2021). This study investigates the determinants of cryptocurrency exchange defaults by analyzing a sample of 845 cryptocurrency exchanges. The dataset comprises 366 default and 479 non-default cryptocurrency exchanges from around the world until February 2023. It employs logit and probit models to identify the significant variables that affect exchange defaults. The findings reveal that centralized cryptocurrency exchanges, located in countries with high transparency indexes, and offer a limited range of cryptocurrencies are more prone to default. Furthermore, exchanges that impose high withdrawal fees and do not have restrictions on users from the U.S. are also positively associated with exchange failure. The study underscores the efficacy of traditional statistical techniques such as logit and probit models in predicting bankruptcies among cryptocurrency exchanges, with an accuracy rate of around 81%. To confirm the high predictability of cryptocurrency exchange bankruptcies, it employs a machine learning approach using random forest, SVM, GBM, neural networks, naive Bayes, and SEM. The results indicate that the random forest technique with the appropriate proportion of training and testing data could be an excellent predictor. The support vector machine approach, on the other hand, does not significantly improve the prediction compared to the logit and probit models. Furthermore, the k-fold cross validation test also confirms the predictive power of all the proposed models.

Thirdly (*iii*), from the practitioners' perspective, the findings of this research suggest that while regulatory oversight is essential, it may not be sufficient to ensure stability. Instead, emphasis should be placed on implementing user-friendly fee structures, robust compliance measures, appropriate user restrictions, and coin diversification to enhance the operational resilience of cryptocurrency exchanges. Implementing a referral program and obtaining ratings from a trusted party can also contribute to the survival of cryptocurrency exchanges. Besides these results, implementing robust security measures, such as multi-factor authentication and encryption, can significantly enhance the security of cryptocurrency exchanges. Furthermore, adhering to regulatory requirements, such as KYC (know your customer) and AML (anti-money laundering) regulations, can enhance the credibility of cryptocurrency exchanges, reduce the risk of fraudulent activities, and prevent illegal transactions. Additionally, ensuring sound financial management practices, such as conducting regular audits, maintaining adequate reserves, and implementing risk management strategies, can enhance the financial sustainability of cryptocurrency exchanges.

This paper is organized as follows: The next section provides a literature review. The third section presents the data and methodologies. Furthermore, the fourth section documents the results and discussions and the last section concludes.

2. Literature review

Bankruptcy is a complex issue that has been studied extensively by researchers over the past few decades (Altman, 1968; Altman et al., 1977, 1995; Lugovskaya, 2010; Wang et al., 2020; etc.). In traditional markets, bankruptcies are often caused by excessive debt, declining revenues, and mismanagement. However, bankruptcies in traditional markets have been declining in recent years due to factors such as economic growth, government support programs, and low-interest rates. Unfortunately, the COVID-19 pandemic has caused a significant increase in unemployment and business failures globally, Zhang et al. (2020). Regardless of the economic situation, bankruptcies in blockchain-based digital financial markets, including cryptocurrencies and crypto tokens defaults, have been on the rise due to scams, hackings, and failures (Grobys and Sapkota, 2020; Grobys et al., 2022a,b).

The bankruptcy literature has predominantly focused on accounting-based financial ratios and mathematical models for bankruptcy prediction. Since the publication of the pioneering study by Beaver (1966), which employs univariate ratio analysis, various bankruptcy prediction models based on financial ratios have been proposed. Altman (1968) uses financial statement data to build a multivariate discriminant analysis (MLDA). After that, logit regression (for example, Ohlson (1980), Platt and Platt (1990), Tseng and Lin (2005)) and probit regression (for example, Zmijewski (1984)) have been widely adopted in subsequent works. Advanced machine learning models have been gaining popularity, as they improve prediction accuracy by utilizing varying proportions of data for training. Despite this, a continuing debate persists regarding the superiority of machine learning methods over conventional statistical techniques (for example, Galindo and Tamayo, 2000; Chatzis et al., 2018).

Bankruptcies and defaults in the new blockchain-based digital financial markets arise due to issues such as poor security practices, insufficient regulation, and fraudulent activity. Sapkota (2022a) highlights 13 different sides (tridecagon) of cryptocurrency risks and shows solvency or default risk as one of them. As the digital financial market continues to evolve, it is likely that we will see continued bankruptcies and defaults, as well as efforts to address the underlying issues that contribute to these events. Therefore, bankruptcies in both traditional and blockchain-based digital financial markets are complex issues that are influenced by a wide range of factors. While bankruptcies in traditional markets have been declining in recent years, bankruptcies in the digital financial markets, especially the cryptocurrency sector, have been on the rise due to factors such as high volatility, hacks, and business failures, among others. One of the main reasons for the increase in cryptocurrency-related bankruptcies is the lack of regulation in the industry. Many cryptocurrency exchanges and projects operate in a legal gray area, making it difficult for investors and regulators to hold them accountable. In addition, the high volatility of cryptocurrency prices can lead to sudden and significant losses for

Table 1
Literature review summary table.

Title	Author(s), Year	Research objective	Data & Methodologies	Summary of findings
Theme 1.a: Bankruptcy prediction models in traditional financial markets using financial ratios and traditional statistical methods				
1. The prediction of corporate bankruptcy: A discriminant analysis, 2. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy	Altman (1967, 1968)	To investigate empirically the characteristics of bankrupt corporations and attempt to develop an accurate bankruptcy predictive model	Z-score and multiple discriminant analysis (MDA), utilizing financial and economic ratios	Results indicate that it is possible to successfully classify corporations into either bankrupt of non-bankrupt groups.
ZETA^{TM} analysis: A new model to identify bankruptcy risk of corporations	Altman et al. (1977)	To explore the development of a bankruptcy classification model which incorporates comprehensive inputs with respect to discriminant analysis	Financial statement data and market related measures are transformed along guidelines suggested by traditional security analysis covering the period 1969–1975	Demonstrated improved accuracy in bankruptcy prediction compared to earlier models with potential significant application to credit worthiness assessment, portfolio management, and to external and internal performance analysis.
Financial ratios as predictors of failure	Beaver (1966)	To investigate the effectiveness of financial ratios in predicting business failure.	Moody's industrial manual (1954 to 1964), financial ratio analysis, dichotomous classification test	If ratios are used to detect the financial illness of a firm, one could detect those illness before they occur and prior treatment could be given to save the firms from failing.
Financial ratios and the probabilistic prediction of bankruptcy	Ohlson (1980)	To investigate the effectiveness of financial ratios in predicting bankruptcy.	10-K financial statements, logit model applied to financial data of firms. (1970–76)	Factors affecting probability of failures within one year are; size of the company, a measure of financial structure, a measure of performance and, a measure of current liquidity.
Development of a class of stable predictive variables: the case of bankruptcy prediction	Platt and Platt (1990)	To examine the effects of industry-relative financial and operating ratios and the change in industry output on the likelihood of corporate failure.	Statistics of income (1951–1984), logit model	Models built with industry-relative ratios correctly classified a greater percentage of the sample, both overall and within both subgroups.
Forecasting bankruptcy more accurately: A simple hazard model	Shumway (2001)	To create stable predictive variables for bankruptcy forecasting using multiple-period bankruptcy data	Static Vs. Hazard models, Wall Street Journal Index, Capital Changes Reporter and the Compustat, 300 bankruptcies (1962–1992)	Developed a simple hazard model that uses all available information to determine each firm's bankruptcy risk at each point in time with high accuracy
A quadratic interval logit model for forecasting bankruptcy	Tseng and Lin (2005)	To propose a quadratic interval logistic regression analysis to predict corporate bankruptcies	904 public companies based on the UK (1985–1994), logit model	quadratic interval logit model can indicate which companies will not be bankrupt, which ones will be bankrupt and which ones undetermined.
Theme 1.b: Bankruptcy prediction models in traditional financial markets using machine learning algorithms				
Bankruptcy prediction using synthetic sampling	Garcia (2022)	To provide a solution for data imbalance as the low bankruptcy rates lead to highly imbalanced bankruptcy class distributions, increasing the difficulty of accurately predicting a firm's bankruptcy.	1824 U.S. firms, 41933 quarterly observations (2010–2018), synthetic minority oversampling (SMOTE) with cluster-based undersampling, LDA, naïve bayes, SVM, random forest, and other machine learning algorithms	It shows that classification accuracy significantly improves when the training datasets is balanced using the synthetic minority oversampling technique or one of its extensions.
Credit risk assessment using statistical and machine learning: basic methodology and risk modeling applications	Galindo and Tamayo (2000)	To make a comparative analysis of different statistical and machine learning modeling methods of classification on a mortgage loan data set with the motivation to understand their limitations and potential.	Methodology based on the study of error curves, more than 9000 models as part of the study, machine learning	CART decision-tree, neural networks and the k-nearest neighbor algorithm outperformed the standard probit algorithm.
Forecasting stock market crisis events using deep and statistical machine learning techniques	Chatzis et al. (2018)	To investigate transmission mechanisms across stock markets along with effects from bond and currency markets and predicting stock market crisis episodes	It combines different machine learning algorithms which are presented with daily stock, bond and currency data from 39 countries that cover a large spectrum of economies.	Use of deep neural networks significantly increases the classification accuracy, while offering a robust way to create a global systemic early warning tool.
Theme 2.a: Cryptocurrency exchange market dynamics and decentralization				
Trading and arbitrage in cryptocurrency markets	Makarov and Schoar (2020)	To explore trading and arbitrage opportunities in cryptocurrency markets.	34 exchanges across 19 countries, January 1, 2017, to February 28, 2018.	There are significant barriers to arbitrage between regions and, to a lesser extent, even between exchanges in the same country.
Bitcoin unchained: Determinants of cryptocurrency exchange liquidity	Brauneis et al. (2022)	To examine how price deviations between exchanges emerge	Analyzes the relation between net order flows and prices in the cryptocurrency market.	Found that market depth and transaction costs are key determinants of exchange liquidity.
Arbitrage behavior amongst multiple cryptocurrency exchange markets	Grone et al. (2021)	To investigate the possibility of engaging in arbitrage using publicly available cryptocurrency exchange rates to determine how often arbitrage is possible.	Bitcoin, Ether, and ZCash from July 1, 2017, to 12:00 am November 27, 2020 with hourly data, Bellman-Ford based algorithm	Lower exchange fees facilitate arbitrage in the short run as price variations on different markets are more likely to enable arbitrage.
The rise of decentralized cryptocurrency exchanges: Evaluating the role of airdrops and governance tokens	Makridis et al. (2023)	To investigate the role of airdrops and governance tokens as mechanisms for expanding the base of users and driving up the value of an exchange.	Based on data collected from a popular crypto-asset data aggregation service and manually collected data	Provided preliminary evidence that both airdrops and governance mechanisms are effective for expanding and strengthening networks, particularly for decentralized exchanges.
Decentralized Cryptocurrency Exchange: A Proof-of-Concept based on hashed timelock contracts	Andersson et al. (2018)	To propose a protocol for exchange between cryptocurrencies.	Three parameters — delay, cost and trading pairs.	The protocol is proven to be a possible alternative to the solutions offered today. The prototype displays a proof-of-concept of a decentralized platform that implements this protocol.
The elephant in the dark: a new framework for cryptocurrency taxation and exchange platform regulation in the U.S.	Caliskan (2022)	To propose an evidence-based framework for designing a novel regulation and taxation approach to cryptocurrencies and their markets by using the U.S. as case study.	Two years of fieldwork, surveys, as well as big data analysis of the most valuable 100 cryptocurrencies' white papers	Proposes a meta policy change on regulation and taxation in relation to data money economies.
Nothing but noise? Price discovery across cryptocurrency exchanges	Dimpfl and Peter (2021)	To examine the price discovery contributions of cryptocurrency exchanges in the presence of market microstructure noise	Draw on the information leadership share proposed by Putniņš (2013)	Finds that Bitfinex is the leader in the price discovery process.

(*continued on next page*)

investors, making it challenging to maintain financial stability. In this regard, Grobys et al. (2021) argue that even stablecoins are not stable.

Table 1 (*continued*).

Theme 2.b: Cryptocurrency exchange collapse, closure, bankruptcies, and predictions				
Systemic risks in the cryptocurrency market: Evidence from the FTX collapse	Jalan and Matkovskyy (2023)	To analyze the systemic risk due to FTX cryptocurrency exchange failure	CATFIN to measure systemic risk for the top 100 cryptocurrencies over the period 1/01/2019–28/11/2022.	The FTX crisis did not engender higher systemic risks in this market compared to previous negative shocks. The FTX crisis represents failures in corporate governance and regulatory oversight, rather than cryptos itself.
The collapse of the FTX exchange: The end of cryptocurrency's age of innocence	Conlon et al. (2023)	To outline the key events that led to the bankruptcy of FTX while examining industry-wide implications as a consequence of an acute risk management failure	FTX Balance sheet, value at risk, conditional value at risk	Finds severe risk and liquidity imbalances between the assets and liabilities of FTX, which contributed to the collapse of the exchange and subsequently led to contagion effects across a range of financial market products
FTX collapse: a Ponzi story	Fu et al. (2022)	To study why FTX could not sustain the Ponzi game	Extracts and demonstrates the three drivers of the FTX collapse, FTT, leverage, and diversion.	The crisis of FTX is not an isolated event; it consequently results in the collapse of a chain of associated companies in the entire market.
Understanding the FTX exchange collapse: A dynamic connectedness approach	Akyildirim et al. (2023)	To investigate pathways in which the collapse of the FTX cryptocurrency exchange created spillovers to other assets significantly connected to FTX	Contagion by considering the connection of FTX to other assets via its associated tokens FTT Token (FTT) and Serum (SRM), TVP-VAR dynamic connectedness analysis	Sources of contagion stem from these two tokens created by the FTX exchange.
Crypto exchanges and credit risk: Modeling and forecasting the probability of closure	Fantazzini and Calabrese (2021)	To analyze the determinants surrounding the decision to close an exchange	144 exchanges (Until April-2021), Credit scoring and machine learning techniques	Cybersecurity grades, having a public developer team, the age of the exchange, and the number of available traded cryptocurrencies are important factors
Cryptocurrency exchanges: Predicting which markets will remain active	Milunovich and Lee (2022)	To analyze the factors that keeps the cryptocurrency exchanges alive	238 exchanges (2018–2021), machine learning techniques	find that exchange lifetime, transacted volume, and cybersecurity measures such as security audit, cold storage, and bug bounty programs rank high in terms of feature importance across multiple algorithms.
Cryptocurrency Exchange Closure Revisited (Again)	Mukherjee and Moore (2022)	To analyze the factors that affect cryptocurrency exchanges closure	822 exchanges (2010–2022), logistic regression	Exchanges that only trade cryptocurrencies and not fiat face approximately 60% greater odds of shutting down than those that trade both. Trading more coins is negatively associated with failure.

Previous studies on blockchain-based digital financial markets have specifically examined risks associated with cryptocurrencies and bankruptcies (for example, Liu et al., 2022; Grobys and Sapkota, 2020; Sapkota, 2022a,b). Although empirical evidence indicates that the majority of cryptocurrency exchanges eventually default, there are relatively few studies on the predictability of such failures (for example, Fantazzini and Calabrese, 2021; Milunovich and Lee, 2022). Many previous research studies have examined the impact of cryptocurrency exchange failures (for example, Kokorin et al., 2020; Fu et al., 2022; Jalan and Matkovskyy, 2023; Akyildirim et al., 2023) on different asset markets and risk spillovers. Andersson et al. (2018) propose a decentralized exchange model based on hashed timelock contracts, presenting it as a secure alternative to centralized exchanges prone to attacks. Nevertheless, being able to forecast potential cryptocurrency exchange defaults is important, given the substantial sums of money involved. The continued advancement of more accurate prediction models is relevant to regulators, practitioners, and academics (see Shumway, 2001). Thus, improved modeling and measurement of a firm's default risk can have broad applications for financial market participants. Further research is needed to understand these trends better and develop effective strategies to mitigate the risk of defaults in these markets.

The articles reviewed in this study on bankruptcy prediction are categorized into four distinct themes, as summarized in Table 1. In *Theme 1.a*, traditional approaches like those by Altman (1967, 1968), Beaver (1966) and Ohlson (1980) employ financial ratios and statistical models to predict corporate bankruptcy with significant accuracy. These models have been refined with advanced techniques such as logit and hazard models (for example, Platt and Platt, 1990; Shumway, 2001). *Theme 1.b* explores the use of machine learning, with studies by Garcia (2022) and Galindo and Tamayo (2000) demonstrating that algorithms, such as SMOTE and neural networks improve prediction accuracy for bankruptcy.

In *Theme 2.a*, research on cryptocurrency markets focuses on trading dynamics and decentralization, revealing factors like arbitrage opportunities and exchange liquidity (Makarov and Schoar, 2020; Brauneis et al., 2022). *Theme 2.b* addresses cryptocurrency exchange collapses, notably the FTX collapse, emphasizing the systemic risks and governance failures (Jalan and Matkovskyy, 2023; Conlon et al., 2023). This literature highlights the evolving strategies in financial prediction and the complexities of managing risks in both traditional and emerging markets. More recently, Fantazzini and Calabrese (2021), Milunovich and Lee (2022) and Mukherjee and Moore (2022) implement traditional statistical models, machine learning models, or both to analyze the probability of cryptocurrency exchange closure.

3. Data and methodologies

3.1. Preparing the data set

The data used in this study is downloaded from three different websites, namely: Coinmarketcap.com, Cryptowisser.com, and Coingecko.com. As of today (10.4.2023), the most popular cryptocurrency price tracking website Coinmarketcap.com has a list of 609 running cryptocurrency exchanges. Cryptowisser.com has a list of 405 default and 425 running cryptocurrency exchanges. The third website, Coingecko.com, has a list of 638 cryptocurrency exchanges, tracked for different trust scores or certification test

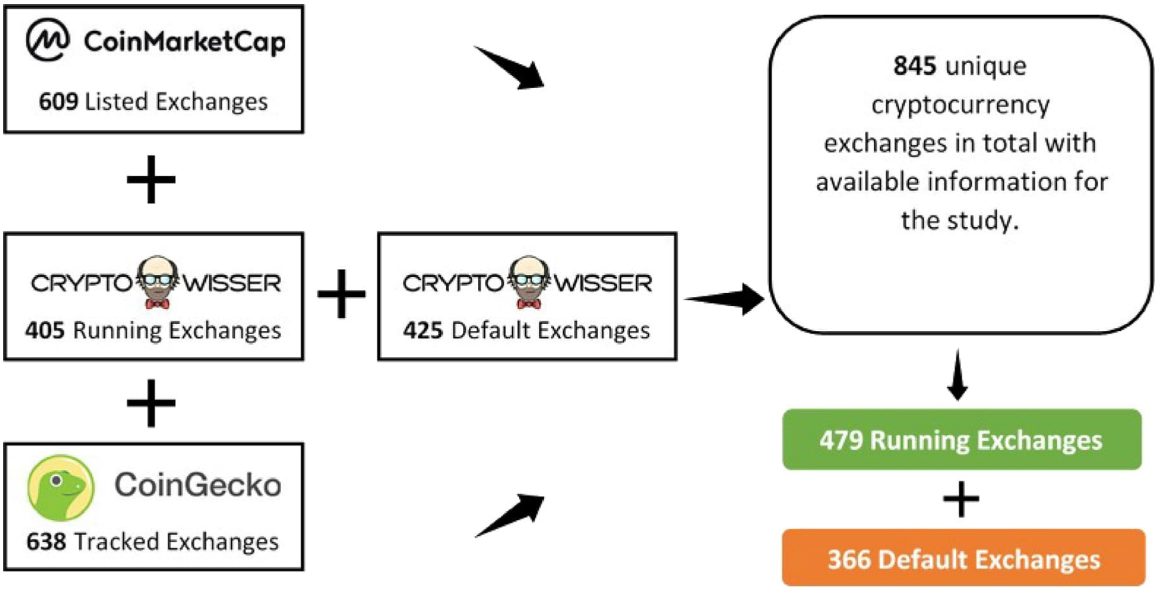

Fig. 1. Cryptocurrency exchange data accumulation process (2010-Feb 2023). **Note**: This figure illustrates the data accumulation process for cryptocurrency exchanges from 2010 to February 2023. It visually represents the collection of data for 845 unique exchanges, using three different sources, as well as the processing and categorization into Running and Default exchanges.

information. There might be concerns about the reliability of data provided by these platforms. To address this, Vidal-Tomás (2022) conducts an in-depth analysis of various cryptocurrency data sources and finds that coin-ranking sites, such as CoinMarketCap, CoinGecko, and BraveNewCoin, are suitable for research purposes. It highlights that these platforms capture the majority of cryptocurrency trading activity and share underlying processes with major exchange platforms like Coinbase and Bitstamp, as well as with alternative ranking sites like Cryptocompare.

From the list of a total of 2077 cryptocurrency exchanges extracted from the websites mentioned in Fig. 1 above, 845 exchanges are unique. After screening for the 425 exchanges marked as default by Cryptowisser.com, this results in 366 defaulted exchanges that include all the variable information. Thus, the fairly distributed data sample consists of 479 operational exchanges and 366 defaulted exchanges, respectively.

Cryptocurrency exchanges have seen a surge in popularity in recent years, but not all exchanges have been able to survive. Fig. 2, on running and default cryptocurrency exchanges from around the world, provides some interesting insights. The graph shows that Singapore has the highest number of default exchanges (41), followed by Hong Kong (29). On the other hand, Singapore also has a high number of running exchanges with 55, indicating that the country has a vibrant cryptocurrency exchange industry. In terms of continents, Asia has the highest number of running exchanges with a total of 129, while Europe has the highest number of default exchanges with 60. The data suggests that Asia may offer a more conducive environment for running cryptocurrency exchanges, while Europe might face more regulatory challenges, contributing to a higher default rate. When it comes to developed versus developing countries, the data shows that both types of countries have their fair share of running and default exchanges. The United Kingdom, the U.S., and Australia all have an equal number of running and default exchanges, indicating that developed countries are not immune to the risk of default. Similarly, developing countries like Seychelles and developed countries like Estonia have a high number of running exchanges, suggesting that both can provide a favorable environment for cryptocurrency exchanges. Overall, the figure suggests that the cryptocurrency exchange industry is still in its early stages and faces significant risks. Nonetheless, countries that can provide a supportive regulatory environment and attract investment have the potential to develop a vibrant exchange industry, regardless of their level of development.

In Figs. 3 and 4, the trends in cryptocurrency exchanges defaulting for various reasons are clearly observable. Between 2014 and February 2023, defaults occurred due to business issues, hacking, disappearance, rebranding, regulatory challenges, and scams. Fig. 4 highlights that after 2018, most cryptocurrency exchanges defaulted without specific reasons, disappearing from the market and leaving clients in disarray. During the 2014–2023 period, business issues, regulatory challenges, and scams contributed almost equally to the failures of cryptocurrency exchanges worldwide.

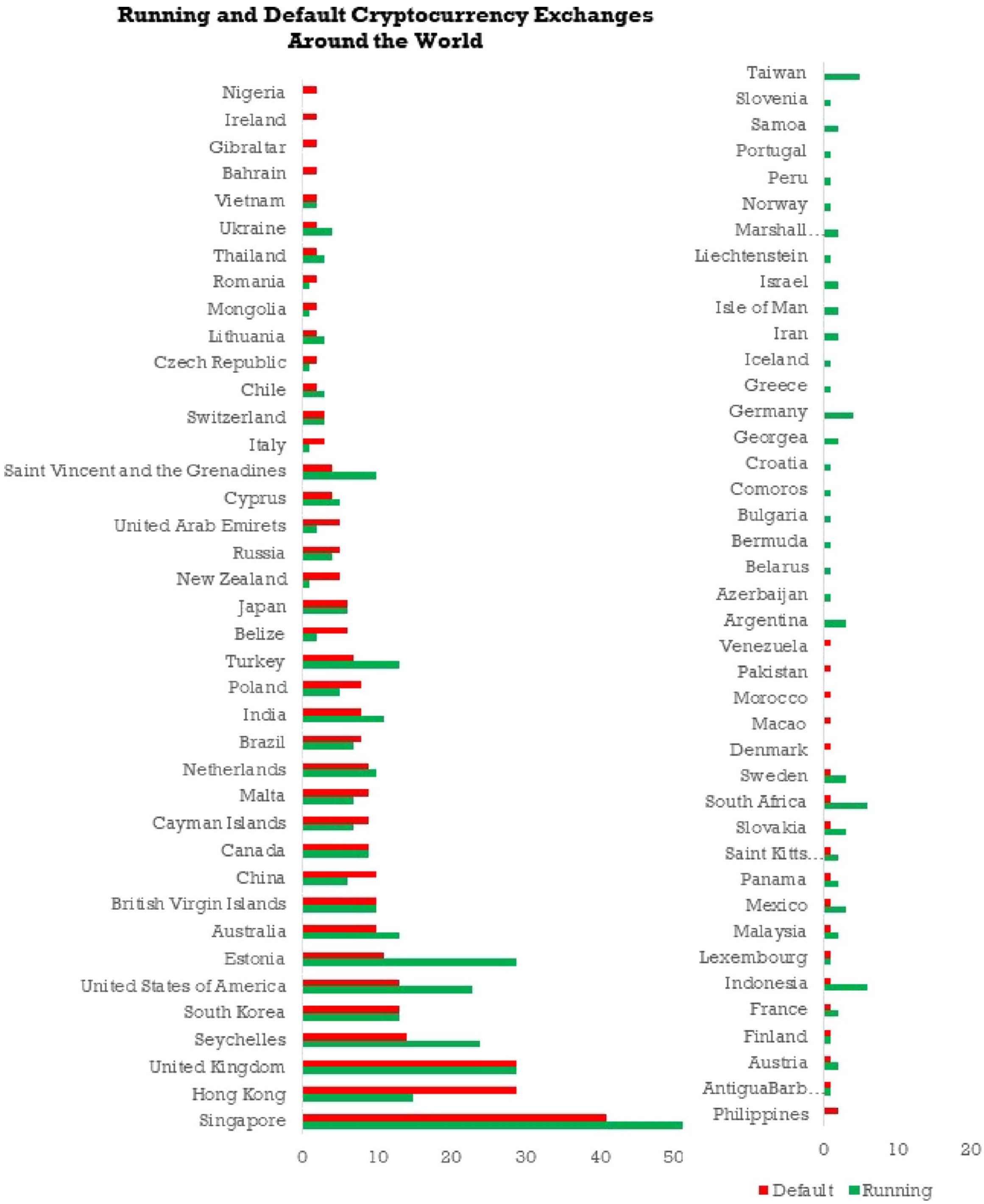

Fig. 2. Cryptocurrency exchanges around the world (2010-Feb 2023). **Note**: This histogram shows the number of default and running cryptocurrency exchanges worldwide from 2010 to February 2023. The red bars represent the number of default exchanges, while the green bars represent the number of running exchanges across different countries. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

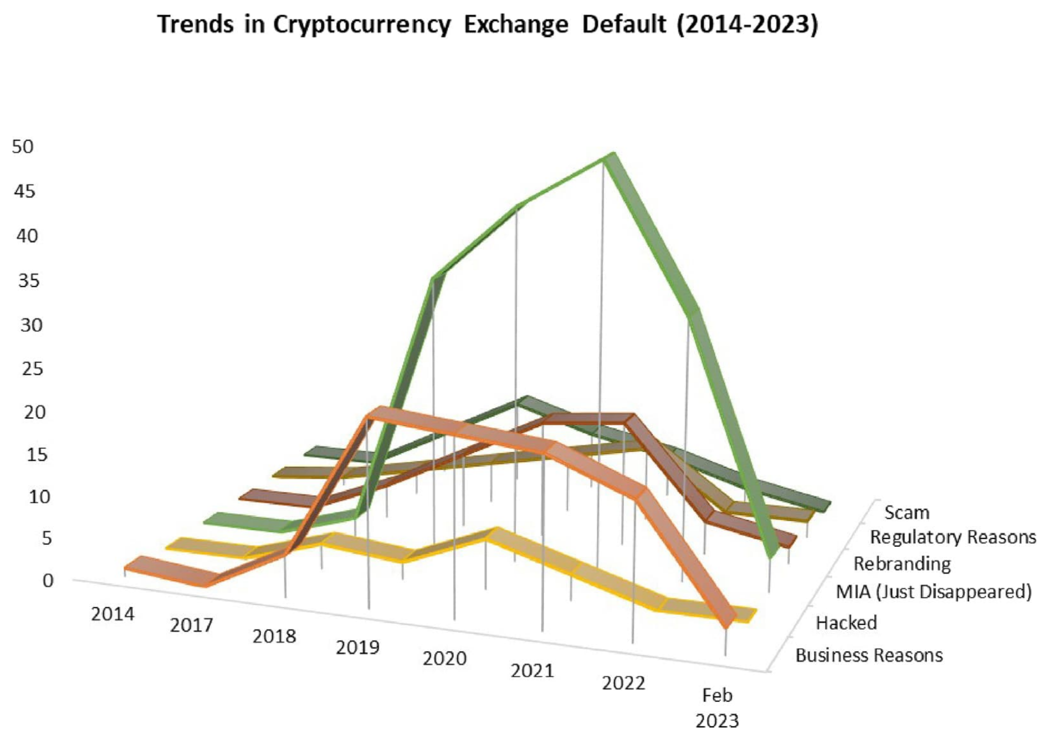

Fig. 3. Trends in the reasons behind cryptocurrency exchange failures (2014–2023). **Note**: This line graph displays trends in the various reasons behind cryptocurrency exchange defaults from 2010 to February 2023. The classification of default causes is based on information provided by the website cryptowisser.com.

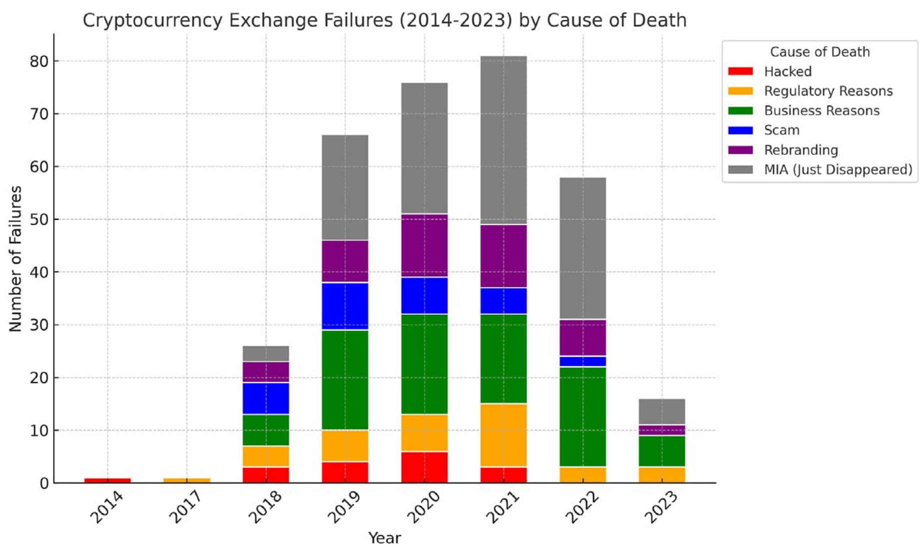

Fig. 4. Reasons behind cryptocurrency exchange failures (2014–2023). **Note**: This histogram shows the magnitude of various reasons behind cryptocurrency exchange defaults from 2014 to February 2023. The classification of default causes is based on information provided by the website cryptowisser.com. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.2. Identifying the variables

This study identifies 17 distinct variables related to 845 global cryptocurrency exchanges, which are publicly available as open-source data and can be easily accessed, even by novice investors. Table A.1 in the Appendix provides a comprehensive list of all variables used in this study, along with their descriptions and data sources. The variable *Status* is a binary indicator that denotes whether an exchange is operational or has defaulted. A default exchange is one that has ceased operations, faced financial difficulties, or been declared bankrupt.

DEX is an indicator variable of whether the exchange is a decentralized exchange or not (i.e centralized). This variable is significant for predicting exchange bankruptcy as decentralized exchanges typically operate differently from centralized ones. The decentralized nature of an exchange can affect its stability, governance, and regulatory compliance, which can have implications for financial viability. For example; Barbon and Ranaldo (2021) aruge that Uniswap v3, the most recent DEX upgrade, has significantly enhanced the quality of decentralized cryptocurrency exchange market.

No_cryptos represents the number of cryptocurrencies listed on the exchange. The number of cryptocurrencies available on an exchange can impact its revenue potential, trading volume, and attractiveness to users. Therefore, this variable plays a role in predicting exchange failure as it relates to the exchange's ability to generate income and sustain operations. *Wire* is an indicator of whether the exchange supports wire transfer or not. Wire transfers are a common method for depositing and withdrawing funds. The availability of wire transfer support can influence the ease of use and accessibility of an exchange. This variable is relevant for predicting exchange default, as it relates to the exchange's ability to facilitate fund transfers. *Credit* is an indicator of whether the exchange supports credit card deposits, which offer convenience to users but can also introduce additional risks such as chargebacks. The availability of credit card support can impact user adoption and transaction volume, which has implications for the financial stability of the exchange. Fantazzini and Calabrese (2021) use the number of tradable assets, wire transfer and credit card transfer possibilities to analyze the credit risk of the cryptocurrency exchanges.

Taker_rate refers to the taker fee rate, which is the fee paid by the person taking an offer. The fee structure of an exchange is an important factor in its revenue generation. Higher taker fees may affect trading activity and user participation, potentially impacting the financial health of the exchange. Thus, this variable is relevant for predicting exchange default. Similarly, *Maker_rate* variable represents the maker fee rate, which is the fee paid by the person making an offer. Similar to the taker fee rate, the maker fee rate influences the revenue generation of an exchange. The fee structure affects the profitability of market makers and can impact trading volume and liquidity, Brauneis et al. (2022) and Galati (2024). Therefore, this variable is also important for this study. Moreover, *Withdrawal_fee* variable denotes the fee in BTC (Bitcoin) for withdrawal. Withdrawal fees can affect user behavior and participation in an exchange. Higher withdrawal fees might discourage users from withdrawing funds, which can impact liquidity and potentially signal financial difficulties. Hence, this variable contributes to predicting cryptocurrency exchange default.

U.S._allow variable is an indicator of whether the exchange allows U.S. customers or not. The regulatory landscape and compliance requirements for serving U.S. customers can be complex and stringent. The ability to serve U.S. customers can impact market reach and potential revenue streams. Therefore, this variable is important for predicting cryptocurrency exchange default, as it relates to regulatory risks and market opportunities. Feinstein and Werbach (2021) argue that traders may not always find it easy to move their activities across borders. For instance, the U.S. applies its regulations extraterritorial if trading involves or targets U.S. citizens. As a result, some U.S. policy announcements may prompt foreign exchanges to restrict access to American traders, even if the regulations in their own countries are more relaxed.

Rating represents an evaluation covering various aspects of an exchange, including product quality, infrastructure, user accounts, and security. This variable is important for predicting exchange default risk, as lower ratings may indicate weaknesses in critical areas, potentially increasing the risk of financial difficulties or failure. Borri and Shakhnov (2022) select exchanges based on a range of quality indicators such as ratings, web traffic data, and liquidity to ensure the exchanges in their sample are not those flagged for fake volume or non-economic wash trading.

Affiliation indicates whether the exchange has an affiliation program or not. An affiliate program allows individuals or organizations to earn commissions or rewards for referring new users to the platform. The presence of an affiliate program can contribute to user acquisition and platform growth. It can also indicate marketing and expansion strategies of the exchange. Thus, this variable is relevant for predicting cryptocurrency exchange default, as it relates to the exchange's ability to attract and retain users. Moreover, Xia et al. (2020) identify 1595 scam domains targeting 58 cryptocurrency exchanges, representing 83% of the exchanges analyzed. Referral Fraud is the most prevalent category, accounting for 52.41% of all scam domains. In this context, the affiliation program has both positive and negative aspects, which can influence the survival or failure of cryptocurrency exchanges.

Certification variable represents whether the exchange has been certified or not. Certification refers to the acknowledgment or endorsement of the exchange's adherence with certain standards or regulations. Certification can provide assurance to users regarding the exchange's security, transparency, and operational practices. The presence of certification can influence user trust and confidence, which is vital for the exchange's sustainability and viability. *Pen_test* variable is an indicator of whether the exchange has undergone a penetration test or not. Penetration testing involves evaluating the security of a system by simulating real-world attacks. By conducting penetration tests, exchanges can identify vulnerabilities and strengthen their security measures. The presence of penetration testing indicates the exchange's proactive approach to security and risk mitigation, which is crucial for preventing financial losses and bankruptcy. According to Coingecko.com, the *POR* (proof of reserves) variable covers two fundamental certification test measures;

i *Identifiable wallets:* All wallet addresses owned by the cryptocurrency exchange must be publicly disclosed and provable on blockchain explorers.

ii *Minimum funding limit:* Certification of cryptocurrency exchanges will only be conducted for exchanges with a wallet balance of more than $1 million U.S. dollars (USD) (in ETH and BTC terms).

If both of these criteria are matched, *POR* is a dummy variable assigned as an indicator of whether the exchange has Proof of Reserves or not.

BBounty variable is an indicator of whether the exchange has a bug bounty program or not. Bug bounty programs incentivize security researchers to identify and report vulnerabilities or bugs in exchange systems. The presence of a bug bounty program demonstrates the exchange's commitment to maintaining a robust and secure platform. By addressing potential security vulnerabilities, the exchange can safeguard user assets and its reputation, thereby mitigating the risk of bankruptcy due to security breaches or losses. From the list of predictors on whether the cryptocurrency exchange will survive or not, Milunovich and Lee (2022) show that cyber-security measures such as security audit and bug bounty programs rank high in terms of feature importance across multiple machine learning algorithms. Cryptocurrency exchanges are generally evaluated for security, transparency, and operational standards by meeting several criteria, often including penetration testing, proof of reserves, and bug bounty programs.

Transparency variable represents the transparency index of the home country where the exchange is registered. Transparency index measures the level of transparency and accountability in a country's governance and financial systems. The transparency index of the exchange's home country can provide insights into the regulatory environment, legal frameworks, and potential risks. Higher transparency indices generally indicate a more favorable regulatory climate, which can contribute to the exchange's stability and long-term viability. However, for the decentralized exchanges, indicating this variable is challenging. Since some of the decentralized cryptocurrency exchanges do not have a home country a global average of the transparency indices during the bankruptcy year of the particular cryptocurrency exchange is assigned. According to Bhimani et al. (2022), there is a negative correlation between cryptocurrency adoption and factors such as the economic freedom index, democracy, control of corruption, and the human development index. This suggests that countries with established liberal economic policies, transparent governance, and high levels of human development may already have robust infrastructure in place. As a result, the cost of replacing these existing systems could outweigh the potential benefits offered by cryptocurrencies.

Control_Age is a control variable crucial to mitigate survivorship bias. Survivorship bias may arise when we consider the entities that have survived in our dataset, potentially leading to distorted risk assessments. By incorporating age as a control variable, we account for the varying ages of entities in our data and the potential evolution of their default risk. While Fantazzini and Calabrese (2021) and Milunovich and Lee (2022) use age as one of the main predictive variables and show older exchanges are less likely to fail, we use it as a control for the survivorship bias.

In addition to the variables mentioned, incorporating the average daily trading volume of cryptocurrency exchanges could provide deeper insights into the role of liquidity and the financial health of these exchanges. Unfortunately, collecting this data, particularly for exchanges that have ceased operations, is challenging due to their disappearance and inactive websites. Furthermore, the data source Cryptowisser does not provide records on trading volumes for these exchanges. Addressing this gap in future research could enhance the analysis of cryptocurrency exchange survival. Additionally, if time-series datasets were available, including Bitcoin volatility as a fixed effect could account for time dynamics and potential idiosyncratic effects arising from macroeconomic differences not captured by the variables in this study (Yamak et al., 2019).

Table 2 presents the descriptive statistics of the whole, running, and default cryptocurrency exchanges. As a whole, cryptocurrency exchanges have on average around 48 cryptocurrencies. The mean taker rate is 0.5%, and the mean maker rate is 0.41%. On average, the exchanges have been in operation for almost four and half years, and their ratings have a mean of 0.31. Panel B shows that the running cryptocurrency exchanges have on average a higher number of cryptocurrencies at 63. The mean taker rate is 0.62% and the maker rate is 0.52%. The running exchanges have a higher mean rating of 0.51, and they have been in operation for an average of five and a half years. Panel C shows that the default cryptocurrency exchanges have on average lower number of cryptocurrencies at 27. The mean taker rate is 0.35%, and the mean maker rate is 0.27%. The default exchanges have a lower mean rating of 0.06, and they have been in operation for an average of almost 3 years.

One may contend that the centralization component in the previously mentioned exchanges contributed to their eventual failures, as decentralized exchanges (DEXs) do not hold users' funds and are thus less susceptible to hacks and thefts that affect centralized exchanges (CEXs). While the argument seems valid, DEXs still face technical challenges and regulatory obstacles. DEXs are a type of exchange that allows users to trade cryptocurrencies directly with each other without the need for a central authority. They typically do not hold users' funds, as trades are executed through smart contracts on the blockchain. Exchanges such as Uniswap, Kyber Network, and Bancor operate on a peer-to-peer (P2P) network without intermediaries or a central authority. In contrast, CEXs, such as Binance, Coinbase, Kraken, and Bitstamp, function similarly to traditional stock exchanges and are managed by a central authority that stores users' assets in a centralized database. Yet, the failure of a DEX could still have several potential impacts. One possible impact is a loss of trust and confidence in the broader decentralized exchange ecosystem. Users may be hesitant to use other DEXs, which could lead to a decline in trading volume and liquidity. This could make it more difficult for users to buy and sell cryptocurrencies, and could also affect the value of individual cryptocurrencies. Another possible impact of a DEX going into default is increased regulatory scrutiny. Regulators may view the default as a sign that decentralized exchanges are not secure or reliable, and may take steps to impose new regulations or restrictions on the industry. This could make it more difficult for DEXs to operate and could limit the growth of the DeFi ecosystem as a whole. While the bankruptcy of a DEX may not directly result in the loss of users' funds, it could still have significant impacts on the cryptocurrency industry and the broader economy. For example, EtherDelta, considered to be the first decentralized exchange, was the target of a hack where the attacker altered the site's

Table 2
Descriptive statistics of the whole, running & default cryptocurrency exchanges.

Variables	N	Mean	Std.	Median	Min	Max	Range	Skew	Kurt
Panel A: Descriptive statistics of whole cryptocurrency exchanges									
No_cryptos	845	47.7408	83.6206	16	1	624	623	3.2419	12.4226
Taker_rate	845	0.0050	0.0145	0.0020	0.0000	0.1799	0.1799	6.5788	53.7361
Maker_rate	845	0.0041	0.0132	0.0010	0.0000	0.1799	0.1799	7.5978	73.1997
Withdrawal_fee	845	0.0005	0.0007	0.0004	0.0000	0.0080	0.0080	5.0214	39.0386
Ratings	845	0.3148	0.8334	0	0	3	3	2.5807	5.1830
Transparency	845	60.5201	19.0525	62.0000	15.3300	89.4200	74.0900	−0.3400	−1.0600
Status	845	0.4331	–	–	–	–	–	–	–
DEX	845	0.1562	–	–	–	–	–	–	–
Certification	845	0.1467	–	–	–	–	–	–	–
Wire	845	0.5420	–	–	–	–	–	–	–
Credit	845	0.3077	–	–	–	–	–	–	–
U.S._allow	845	0.6521	–	–	–	–	–	–	–
Affiliation	845	0.2012	–	–	–	–	–	–	–
Control_Age	845	4.4746	2.5539	4	0	16	16	0.8118	0.5353
Panel B: Descriptive statistics of running cryptocurrency exchanges									
No_cryptos	479	63.2443	98.3554	22	1	624	623	2.5006	6.8677
Taker_rate	479	0.0062	0.0170	0.0020	0.0000	0.1799	0.1799	5.8522	42.3023
Maker_rate	479	0.0052	0.0157	0.0015	0.0000	0.1799	0.1799	6.7310	56.3998
Withdrawal_fee	479	0.0004	0.0004	0.0003	0.0000	0.0050	0.0050	3.9335	30.4864
Ratings	479	0.5115	1.0286	0	0	3	3	1.7588	1.4192
Transparency	479	59.9419	18.8380	62.0000	15.3300	88.8300	73.5000	−0.2769	−1.0887
DEX	479	0.1837	–	–	–	–	–	–	–
Certification	479	0.2296	–	–	–	–	–	–	–
Wire	479	0.5950	–	–	–	–	–	–	–
Credit	479	0.3486	–	–	–	–	–	–	–
U.S._allow	479	0.6138	–	–	–	–	–	–	–
Affiliation	479	0.2672	–	–	–	–	–	–	–
Control_Age	479	5.6117	2.4028	5	1	16	15	0.8082	0.3945
Panel C: Descriptive statistics of default cryptocurrency exchanges									
No_cryptos	366	27.0575	52.1789	12.0000	1	605	604	6.0187	50.2753
Taker_rate	366	0.0035	0.0100	0.0020	0.0000	0.1000	0.1000	7.3854	60.9840
Maker_rate	366	0.0027	0.0085	0.0010	0.0000	0.1000	0.1000	8.0719	75.0362
Withdrawal_fee	366	0.0006	0.0009	0.0005	0.0000	0.0080	0.0080	4.1819	24.7403
Ratings	366	0.0575	0.3222	0	0	3	3	6.6395	48.7277
Transparency	366	61.2962	19.3523	62.0000	15.3300	89.4200	74.0900	−0.4251	−0.9887
DEX	366	0.1205	–	–	–	–	–	–	–
Certification	366	0.0384	–	–	–	–	–	–	–
Wire	366	0.4712	–	–	–	–	–	–	–
Credit	366	0.2521	–	–	–	–	–	–	–
U.S._allow	366	0.7014	–	–	–	–	–	–	–
Affiliation	366	0.1151	–	–	–	–	–	–	–
Control_Age	366	2.9918	1.8978	3	0	13	13	1.2098	2.3065

Note: This table provides descriptive statistics for cryptocurrency exchanges across three groups: the entire sample (Panel A), running exchanges (Panel B), and defaulted exchanges (Panel C). Variables include the number of listed cryptocurrencies (No_cryptos), taker fees (Taker_rate), maker fees (Maker_rate), and withdrawal fees (Withdrawal_fee), as well as ratings (Ratings) and transparency index of the country where the exchange is registered (Transparency). Binary variables indicate whether the exchange is decentralized (DEX), certified (Certification), supports wire transfers (Wire) or credit card payments (Credit), allows U.S. users (U.S._allow), and has affiliation program (Affiliation). Control_Age represents the age of the exchange in years. 'N' shows the number of exchanges in each category. The data spans from 2010 to February 2023.

domain name system (DNS) settings, redirecting users to a fake version of the site to steal their funds. The exchange was later fined by the SEC for operating as an unregistered securities exchange, and it is now on the list of default cryptocurrency exchanges in cryptowisser.com. DEXs offer numerous advantages, including heightened security and privacy with no central authority controlling users' assets, the risk of a single point of failure is significantly reduced. Users have greater control over their assets since they can directly interact with the smart contract without intermediaries. Unfortunately, there are numerous cases of DEXs failures too, for example; Fcoin Exchange, SparkDEX, StellarDEX, CryptoBridge DEX, Aphelion, OasisDEX, etc.

The mean difference test in Table 3 compares various variables between running and default cryptocurrency exchanges. Significant differences are observed in several aspects. Running exchanges tend to list a significantly higher number of cryptocurrencies and have higher ratings compared to default exchanges, yet no significant differences are observed in transaction fees or in certain features, such as taker and maker rates.

Table 3
Mean difference significance test.

Variables	Running Ex.			Default Ex.			Significance	
	N	Mean	SD	N	Mean	SD	Mean Diff	t-stat
No_cryptos	479	63.2443	98.3554	366	27.0575	52.1789	36.1867	6.469***
Taker_rate	479	0.0062	0.0170	366	0.0035	0.0100	0.0027	1.271
Maker_rate	479	0.0052	0.0157	366	0.0027	0.0085	0.0025	1.298
Withdrawal_fee	479	0.0004	0.0004	366	0.0006	0.0009	−0.0002	−0.719
Ratings	479	0.5115	1.0286	366	0.0575	0.3222	0.4539	9.555***
Transparency	479	59.9419	18.8380	366	61.2962	19.3523	−1.3543	−1.768
Dummy Variables								
DEX	479	0.1837	0.3877	366	0.1205	0.3260	0.0632	1.936
Certification	479	0.2296	0.4210	366	0.0384	0.1923	0.1913	6.325***
Wire	479	0.5950	0.4914	366	0.4712	0.4999	0.1238	2.847**
Credit	479	0.3486	0.4770	366	0.2521	0.4348	0.0966	2.223*
U.S._allow	479	0.6138	0.4874	366	0.7014	0.4583	−0.0876	−2.096*
Affiliation	479	0.2672	0.4430	366	0.1151	0.3195	0.1522	5.601***
Control_Age	479	5.6117	2.4028	366	2.9918	1.8978	2.6199	11.194***

Note: This table reports the mean difference between the variables of the running cryptocurrency exchanges (Running Ex.) and default cryptocurrency exchanges (Default Ex.) across various characteristics. Variables include the number of listed cryptocurrencies (No_cryptos), taker fees (Taker_rate), maker fees (Maker_rate), withdrawal fees (Withdrawal_fee), ratings (Ratings), and transparency index of the home country (Transparency). Binary variables are, decentralized exchange (DEX), certification status (Certification), support for wire transfers (Wire) and credit card payments (Credit), allowance for U.S. users (U.S._allow), and affiliation programs (Affiliation). Control_Age is the age of the exchange in years. The data spans from 2010 to February 2023. For binary (dummy) variables, a two-sample proportion test is done to compare the mean difference, while for continuous variables a two-sample t-test is carried out.
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05.

3.3. Statistical model

Several previous studies on corporate bankruptcies have employed MLDA for classification and prediction purposes (for example, Altman, 1967, 1968). In addition to MLDA, the logit model has also been widely applied (Tseng and Lin, 2005; Platt and Platt, 1990, etc.), with many scholars favoring it over MLDA. McFadden (1984) and Lo (1986) highlight several statistical advantages of the logit model, such as its robustness, flexibility, and interpretability when analyzing categorical choice data. In this study, we use the logit model over MLDA, and implementing probit models allows for conducting robustness checks. By comparing the results from both models, we can ensure that the findings are not overly sensitive to the specific distributional assumptions of one model. If both models yield similar results, it strengthens confidence in the robustness of the findings. Additionally, because logit and probit models are based on different distributions, their comparison can provide insights into the nature of the underlying data. For example, if one model provides a significantly better fit than the other, it might suggest that the assumed distribution of errors in that model aligns more closely with the actual data. Nevertheless, using both logit and probit models allows us to cross-validate the results, ensuring that the conclusions drawn about the factors influencing exchange defaults are not an artifact of the choice of statistical model. This dual approach enhances the credibility and generalizability of the research findings.

3.3.1. Logit model

The logistic regression model, commonly referred to as the logit model, is a popular statistical model for binary outcomes. The model simulates the log-odds or logit transformation of the binary outcome probability. It applies a logistic function to translate the log-odds to a probability between 0 and 1, presuming a linear relationship between the predictors and the log-odds. The logit model enables researchers to examine and comprehend the factors impacting binary outcomes in a number of disciplines, including economics, social sciences, marketing, and healthcare. The logit model equation can be written as:

$$\begin{aligned}\log\left(\frac{P(\text{Status}=1)}{1-P(\text{Status}=1)}\right) = Z\beta_0 + \beta_1\text{DEX} + \beta_2\log(\text{No\_cryptos}) + \beta_3\text{Taker\_rate}+\\ \beta_4\text{Maker\_rate} + \beta_5\text{Withdrawal\_fee} + \beta_6\text{Wire} + \beta_7\text{Credit} + \beta_8\text{U.S.\_allow} + \beta_9\text{Affiliation}+\\ \beta_{10}\text{Ratings} + \beta_{11}\text{Transparency} + \beta_{12}\text{Certification}+\\ \beta_{13}\text{Control\_Age}\end{aligned} \tag{1}$$

where P is the probability of an event occurring, and 1 is the odds of an event occurring. Z is the linear combination of independent variables with coefficients. The above equation can be solved further to arrive at the following function which can be used to determine the probability of occurrence of the events.

$$P = \sigma(z) = \frac{1}{1+e^{-Z}} \tag{2}$$

$\sigma(Z)$ is also called a logistic or sigmoid function. As the value of Z approaches $-(ve)infinity$, the value of $\sigma(Z)$ or P approaches 0. And, as the value of Z approaches $+(ve)infinity$, the value of $\sigma(Z)$ or P approaches 1.

3.3.2. Probit model

Another popular statistical model for binary outcomes is the probit model. Although it is similar to the logit model, it uses the probit function, which is the cumulative distribution function of the regular normal distribution, rather than the logistic function. The probit model presupposes that the error term of the linear regression model has a typical normal distribution. It calculates the effects of different variables on the likelihood of the binary outcome by modeling the link between the predictors and the cumulative probability of the binary outcome. It also offers insights into the determinants and probabilities of binary events or outcomes and has applications in a variety of sectors, including economics, social sciences, and finance. To obtain a probit model, we start with the same equation as in the logit model and assume that the error term in the linear regression model follows a standard normal distribution. The probit model can then be written as:

$$\begin{aligned} P(\text{Status}=1) = \Phi(Z) = \Phi(\beta_0 + \beta_1\text{DEX} + \beta_2\log(\text{No\_cryptos}) + \beta_3\text{Taker\_rate} + \\ \beta_4\text{Maker\_rate} + \beta_5\text{Withdrawal\_fee} + \beta_6\text{Wire} + \beta_7\text{Credit} + \beta_8\text{U.S.\_allow} + \\ \beta_9\text{Affiliation} + \beta_{10}\text{Ratings} + \beta_{11}\text{Transparency} + \beta_{12}\text{Certification} + \\ \beta_{13}\text{Control\_Age}) \end{aligned} \tag{3}$$

where Φ is the cumulative distribution function of the standard normal distribution. In other words, $\Phi(Z)$ gives the probability that a standard normal random variable is less than or equal to Z. If $\Phi(Z)$ is less than 0.5, it means that the estimated probability of "Status" being 1 is less than 50%. In this case, one can interpret it as the model predicting a higher likelihood of the dependent variable "Status" being 0 rather than 1.

Interpreting the coefficients β in the equation allows us to understand the impact of each predictor on the probability of "Status" being 1. For example, a positive coefficient for a predictor suggests that an increase in its value will result in a higher probability of "Status" being 1, while a negative coefficient suggests the opposite. Therefore, the probit model equation provides a probabilistic framework to estimate the likelihood of the dependent variable "Status" being 1 based on the specified predictors.

4. Results and discussions

4.1. Logit model coefficient estimates

Table 4
Coefficients estimate, logit model.

	Estimate	Std.Error	Z-Value	Pr(>|z|)
(Intercept)	3.17052	0.50442	6.29	3.30E−10***
DEX	−1.29082	0.29859	−4.32	1.50E−05***
Log(No_cryptos)	−0.63807	0.17641	−3.62	0.0003***
Taker_rate	8.87427	11.94222	0.74	0.45742
Maker_rate	−38.53824	15.31953	−2.52	0.01188*
Withdrawal_fee	0.02874	0.00871	3.3	0.00097***
Wire	−0.04845	0.21392	−0.23	0.82083
Credit	−0.00165	0.22068	−0.01	0.99405
U.S._allow	0.41975	0.20154	2.08	0.03728*
Affiliation	−0.44197	0.25962	−1.7	0.08868 .
Ratings	−0.72001	0.39204	−1.84	0.06627 .
Transparency	0.01489	0.00516	2.89	0.00388**
Certification	0.15493	0.72959	0.21	0.83184
Control_Age	−6.18791	0.51006	−12.13	2e−16***

Note: This table reports the coefficients estimate and statistical significance levels (based on a two-sided z-test) for the logit model of cryptocurrency exchange status (1 = Default, 0 = Running) as a function of various exchange characteristics, including whether the exchange is decentralized DEX dummy (1/0), the number of cryptocurrencies listed (No_cryptos), fee rates (Taker_rate, Maker_rate), withdrawal fees (Withdrawal_fee), whether the exchange supports wire transfer Wire dummy (1/0) or credit card deposits Credit dummy (1/0), whether U.S. customers are allowed U.S._allow dummy (1/0), affiliation program presence (Affiliation dummy), certification status Certification dummy, transparency index of the home country (Transparency), and a control variable (Control_Age). The data spans from 2010 to February 2023. The logit model is as follows:

$\log\left(\frac{P(\text{Status}=1)}{1-P(\text{Status}=1)}\right) = Z\beta_0 + \beta_1\text{DEX} + \beta_2\log(\text{No\_cryptos}) + \beta_3\text{Taker\_rate} + \beta_4\text{Maker\_rate} + \beta_5\text{Withdrawal\_fee} + \beta_6\text{Wire} + \beta_7\text{Credit} + \beta_8\text{U.S.\_allow} + \beta_9\text{Affiliation} + \beta_{10}\text{Ratings} + \beta_{11}\text{Transparency} + \beta_{12}\text{Certification} + \beta_{13}\text{Control\_Age}$.

The probability of an event occurring is calculated as $P = \sigma(z) = \frac{1}{1+e^{-Z}}$, where $\sigma(Z)$ is the logistic or sigmoid function. As Z approaches negative infinity, $\sigma(Z)$ or P approaches 0, and as Z approaches positive infinity, $\sigma(Z)$ or P approaches 1.

The intercept represents the log odds of success when all other predictors are equal to zero. Std. Error is the standard error of the estimate, and $Pr(>|z|)$ is the two-sided p-value for the z-test of the null hypothesis that the corresponding coefficient is zero.

Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

(Dispersion parameter for binomial family taken to be 1).

Number of Observations: 845.

Null deviance: 1156.26 on 844 degrees of freedom.

Residual deviance: 731.71 on 831 degrees of freedom.

Akaike information criterion (AIC): 759.7.

Number of Fisher Scoring iterations: 5.

McFadden's Pseudo R-squared: 0.36718.

Table 4 presents the results of a logit model used to predict the probability of cryptocurrency exchange default based on various exchange characteristics. The coefficients provide insight into the direction and strength of the relationship between each independent variable and the dependent variable. It represents the log-odds of the event (defaulting) in the absence of any influence from the other predictors. The predictor variables contribute to the linear combination along with the intercept term to determine the log odds of the event. The coefficients associated with the predictor variables represent the change in the log odds for a unit change in the respective predictor, holding all other variables constant. The findings reveal several statistically significant variables associated with cryptocurrency exchange default.

Decentralized exchanges '*DEX*' and a higher number of listed cryptocurrencies have negative and significant coefficients, indicating a lower likelihood of default. Interestingly, variables such as *U.S._allow*, *Transparency*, and *Withdrawal_fee* show positive and significant coefficients, suggesting that exchanges operating from less corrupt countries, allowing U.S. customers, and charging higher withdrawal fees are more prone to default. Conversely, variables including *Taker_fee*, *Wire*, *Credit*, and *Certification* are not statistically significant in predicting exchange defaults. These results provide valuable insights into the factors influencing cryptocurrency exchange default, allowing for the development of targeted risk mitigation strategies. The statistical significance of variables such as *Ratings* and *Affiliation* program is observed at the 10% level. The negative coefficients indicate that having better ratings and implementing an affiliation program are associated with a reduced likelihood of cryptocurrency exchange defaults. These findings suggest that maintaining favorable ratings and establishing an affiliation program can contribute to acquiring new customers and retaining existing ones, thereby enhancing the stability and sustainability of cryptocurrency exchanges.

In Table A.4 in the Appendix, the results of the logit model reveal its effectiveness in correctly predicting the status of cryptocurrency exchanges. Out of the 366 default exchanges, the model accurately identifies 272 of them, while for the running exchanges, 414 are correctly classified. However, there are 94 instances where the model erroneously predicts running exchanges as default, and 65 default exchanges are mistakenly identified as running. The resulting type II error percentage is calculated as 34.56%, indicating the proportion of false negatives in the model's predictions. To ascertain the reliability of this error rate, a 95% confidence interval is computed, resulting in a range of 29.44% to 39.05%. Notably, this interval does not overlap with the 95% confidence interval of the logit model's overall accuracy. This finding suggests that the logit model demonstrates a high level of accuracy in correctly predicting defaults. Overall, the analysis of Table A.4 and the corresponding type II error percentage provide valuable insights into the logit model's performance. The fact that the confidence interval of the type II error does not overlap with the model's accuracy interval strengthens the argument that the logit model is highly capable of accurately predicting default exchanges.

4.2. Probit model coefficient estimates

Table 5 presents the results of a probit model, which utilizes a range of characteristics specific to cryptocurrency exchanges to predict the probability of their default. The coefficients estimate the impact of each independent variable on the dependent variable show similar results to those of the logit model in Table 4. The intercept term represents the baseline probability of default when all other predictors are zero. The coefficients associated with the predictor variables indicate the change in the probability of default for a unit change in the respective predictor, while holding all other variables constant. The findings reveal several statistically significant variables in predicting cryptocurrency exchange default.

DEX and a higher number of listed cryptocurrencies have negative and significant coefficients, indicating a lower likelihood of default. Variables such as *U.S._allow* and *Transparency* show positive and statistically significant coefficients, suggesting that exchanges allowing U.S. customers and located in countries with higher transparency indices are more prone to default. These results provide valuable insights into the factors influencing cryptocurrency exchange default, aiding in the development of effective risk mitigation strategies. The statistical significance of variables such as *Affiliation* and *Ratings* is observed at the 10% level. The negative coefficients for these variables indicate that implementing an affiliation program and maintaining favorable ratings are associated with a reduced likelihood of cryptocurrency exchange defaults, highlighting the importance of these factors in ensuring stability and sustainability.

In Table A.5, in the Appendix, the results of the probit model confusion matrix reveal its effectiveness in correctly predicting the status of cryptocurrency exchanges. Out of the 366 default exchanges, the model accurately identifies 272 of them, while for the running exchanges, 416 are correctly classified. However, there are 94 instances where the model erroneously predicts default exchanges as running, and 63 running exchanges are mistakenly identified as default.

The resulting type II error percentage is calculated at 34.56%, indicating the proportion of false negatives in the model's predictions. The probit model predicts running cryptocurrency exchanges slightly more accurately than the logit model, as indicated by an improved overall accuracy of 81.42%.

In Fig. 5, the receiver operating characteristic (ROC) curves for the logit and probit models are presented. The ROC curve is a graphical representation of the performance of a binary classifier, such as our models, at various classification thresholds. The ROC curve illustrates the trade-off between the true positive rate (sensitivity) and the false positive rate (1-specificity) as the classification threshold is varied. The true positive rate represents the proportion of actual positive cases (defaulted cryptocurrency exchanges) correctly classified as positive by the model, while the false positive rate represents the proportion of actual negative cases (running cryptocurrency exchanges) incorrectly classified as positive. By comparing the ROC curves of the logit and probit models, we can assess their relative performance in distinguishing between defaulted and running cryptocurrency exchanges. A perfect overlap of the ROC curves for the logit and probit models indicates similar overall predictive performance.

Table 5
Coefficients estimate, probit model.

	Estimate	Std.Error	Z-Value	Pr(>|z|)
(Intercept)	1.7886	0.28169	6.35	2.20E−10***
DEX	−0.72885	0.1702	−4.28	1.80E−05***
Log(No_cryptos)	−0.34845	0.10031	−3.47	0.00051***
Taker_rate	5.23766	6.94112	0.75	0.4505
Maker_rate	−22.35467	8.66393	−2.58	0.00987*
Withdrawal_fee	0.01695	0.00492	3.45	0.00057***
Wire	−0.0551	0.12296	−0.45	0.65406
Credit	0.01138	0.12603	0.09	0.92806
U.S._allow	0.2182	0.11543	1.89	0.05871*
Affiliation	−0.25037	0.148	−1.69	0.0907.
Ratings	−0.41024	0.20183	−2.03	0.04209.
Transparency	0.00823	0.00296	2.78	0.00548**
Certification	0.0989	0.3976	0.25	0.80356
Control_Age	−3.46512	0.26794	−12.93	2e−16***

Note: This table reports the coefficients estimate and statistical significance levels (based on a two-sided z-test) for the probit model of cryptocurrency exchange status (1 = Default, 0 = Running) as a function of various exchange characteristics, including whether the exchange is decentralized DEX dummy (1/0), the number of cryptocurrencies listed (No_cryptos), fee rates (Taker_rate, Maker_rate), withdrawal fees (Withdrawal_fee), whether the exchange supports wire transfer Wire dummy (1/0) or credit card deposits Credit dummy (1/0), whether U.S. customers are allowed U.S._allow dummy (1/0), affiliation program presence (Affiliation dummy), certification status Certification dummy, transparency index of the home country (Transparency), and a control variable (Control_Age). The data spans from 2010 to February 2023. The probit model can be written as: $P(\text{Status} = 1) = \Phi(Z) = \Phi(\beta_0 + \beta_1\text{DEX} + \beta_2\log(\text{No\_cryptos}) + \beta_3\text{Taker\_rate} + \beta_4\text{Maker\_rate} + \beta_5\text{Withdrawal\_fee} + \beta_6\text{Wire} + \beta_7\text{Credit} + \beta_8\text{U.S.\_allow} + \beta_9\text{Affiliation} + \beta_{10}\text{Ratings} + \beta_{11}\text{Transparency} + \beta_{12}\text{Certification} + \beta_{13}\text{Control\_Age})$.
where Φ is the cumulative distribution function of the standard normal distribution. In other words, $\Phi(Z)$ gives the probability that a standard normal random variable is less than or equal to Z. If $\Phi(Z)$ is less than 0.5, it means that the estimated probability of "Status" being 1 is less than 50%. In this case, one can interpret it as the model predicting a higher likelihood of the dependent variable "Status" being 0 rather than 1.
The intercept represents the baseline probability of default when all other predictors are equal to zero. Std. Error is the standard error of the estimate. $Pr(>|z|)$ is the two-sided p-value for the z-test of the null hypothesis that the corresponding coefficient is zero.
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.
(Dispersion parameter for binomial family taken to be 1).
Number of Observations: 845.
Null deviance: 1156.3 on 844 degrees of freedom.
Residual deviance: 736.1 on 831 degrees of freedom.
Akaike information criterion (AIC): 764.1.
Number of Fisher Scoring iterations: 6.
McFadden's Pseudo R-squared: 0.36338.

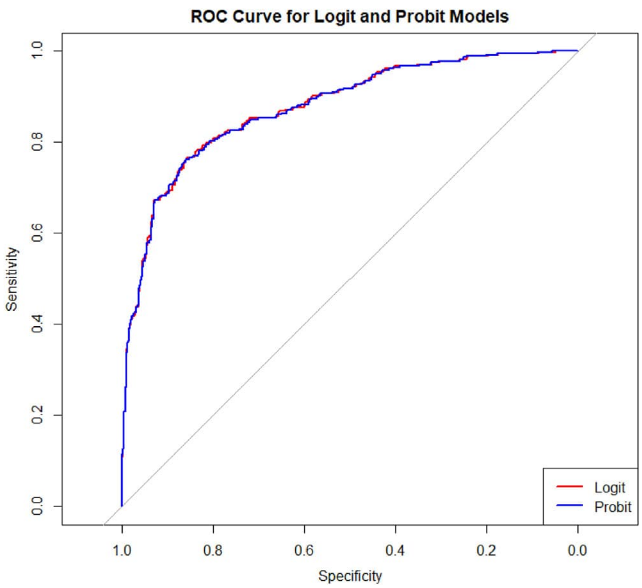

Fig. 5. Receiver operating characteristics curves of logit and probit models. **Note**: The red curve represents the logit model, and the blue curve represents the probit model. The sensitivity shows the proportion of actual positive instances correctly identified by the model (true positives), while the specificity shows the proportion of actual negative instances correctly identified (true negatives). The area under the curve (AUC) is used to evaluate the overall performance of each model, with a higher AUC indicating better predictive ability. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.3. Mean difference test vs. logit and probit model

Differences in significant variable identification are observed between the mean difference tests and the logit model. In Table 3, *Taker_rate*, *Maker_rate*, *Withdrawal_fee*, and *Transparency* show no significant differences between running and defaulted exchanges. Yet, the logit and probit models identify *Maker_rate*, *Withdrawal_fee*, and *Transparency* as significant predictors, as shown in Tables 4 and 5. These disparities can be attributed to the distinct analytical approaches and assumptions employed by each method, variations in the effects of variables, the potential presence of multicollinearity in logistic regression, and the influence of sample size. Mean difference tests focus on comparing means and assume normality and independence, while logistic regression analyzes the relationship between predictors and the probability of an outcome, assuming a logistic distribution. The nature of the outcome variable, underlying assumptions, and statistical power all contribute to the discrepancies in significant variable identification between these two approaches. Careful consideration of these factors is essential when selecting the appropriate analysis method to ensure accurate and reliable results. Therefore, a variable may lack significance in mean difference tests yet still be significant in logistic regression, or vice versa. This is because the mean difference test (t-test or z-test) examines the difference in means between two groups of variables, whereas a logistic regression model examines the relationship between the probability of an outcome and one or more predictor variables, including both continuous and categorical variables.

In the logit model, the effect of a predictor variable on the outcome is measured by its coefficient (i.e., log-odds ratio). The coefficient can be interpreted as the change in the log odds of the outcome associated with a one-unit increase in the predictor variable, holding all other variables in the model constant. A coefficient that is significantly different from zero indicates that the predictor variable has a significant effect on the outcome, even if the mean difference test does not show a significant difference between the groups. The significance of a predictor variable in a logit regression model depends on the model specification and the inclusion of other predictor variables. For example, adding or removing other variables in the model may change the magnitude and significance of the coefficients. Additionally, logit regression assumes a linear relationship between the predictor variable and the log odds of the outcome, which may not always be the case. In these situations, it may be necessary to consider alternative modeling techniques or to transform the predictor variable before including it in the model.

Similar to the logit model, it is also possible for a variable to be significant in the probit model even when the mean difference test does not show a significant difference between the groups. In the probit model, the effect of a predictor variable on the outcome is measured by its coefficient (i.e., the change in the standard normal distribution associated with a one-unit increase in the predictor variable). A significant coefficient in the probit model indicates an effect on the outcome, even if the mean difference test does not detect differences between the groups. In general, probit and logit models are similar in interpretation and analysis. The main difference between the two is the link function used to transform the linear predictor into probabilities or odds. In logit regression, the logit function transforms the linear predictor into the log odds of the outcome. In contrast, probit regression uses the standard normal cumulative distribution function to transform the linear predictor into probabilities.

In the logit model, the *DEX* coefficient of −1.29082 in Table 4 means that holding all other variables constant, the log odds of defaulting for a centralized exchange are significantly higher compared to a decentralized exchange. In other words, decentralized exchanges have a lower probability of defaulting by $e^{-1.29082} \approx 0.275$ or 27.5% when compared to centralized exchanges. This means that the odds of defaulting for decentralized exchanges are 27.5% of the odds for centralized exchanges. Alternatively, decentralized exchanges are 72.5% less likely to default compared to centralized exchanges. Similarly, the coefficient of −0.72885 in the probit model result in Table 5 indicates the change in the standard normal cumulative probability associated with a one-unit increase in the predictor variable, leading to a decrease in the probability of defaulting. Using the standard normal distribution table or statistical software, we can find that the probability of defaulting for a decentralized exchange is lower by approximately 0.312 or 31.2% compared to a centralized exchange.

The *Log(No_cryptos)* variable, representing the logarithm of the number of cryptocurrencies listed on an exchange, has a coefficient of −0.63807 in the logit model results in Table 4. This indicates that as the number of cryptocurrencies increases, the odds of default decrease. Specifically, for every 1-unit increase in the logarithm of the number of cryptocurrencies, the odds of default decrease by approximately $e^{-0.63807} \approx 0.529$, or 47.1%. For example, if a cryptocurrency exchange currently lists 10 cryptocurrencies, the value of *Log(No_cryptos)* is calculated as $\log(10) \approx 2.303$. A one-unit increase in *Log(No_cryptos)* corresponds to an increase from $\log(\text{No\_cryptos}) = 2.303$ to $2.303 + 1 = 3.303$. Converting this back to the actual number of cryptocurrencies, we find $\text{No\_cryptos} = e^{3.303} \approx 27.1$. Therefore, keeping all other factors constant, the odds of default decrease by 47.1% when the number of cryptocurrencies listed increases from 10 to approximately 27. In the probit model in Table 5, the coefficient for *Log(No_cryptos)* is −0.34845, which implies that a 1-unit increase in the log of the number of cryptocurrencies corresponds to a marginal effect that decreases the probability of default by approximately 13.08%, although the exact change depends on the standard normal cumulative distribution and other variables in the model. The *Withdrawal_fee* variable, which measures withdrawal fees, has a coefficient of 0.02874 in the logit model in Table 4, indicating that higher withdrawal fees are associated with an increased probability of default. Specifically, for every 1-unit increase in withdrawal fees, the odds of default increase by approximately $e^{0.02874} \approx 1.029$, or 2.9%. In the probit model in Table 5, the coefficient is 0.01695, reflecting an increase in the latent variable associated with default. This marginal effect corresponds to an approximate 0.68% increase in the probability of default.

The *U.S._allow* variable, which indicates whether the exchange allows U.S. customers, has a coefficient of 0.41975 in the logit model results in Table 4. This suggests that exchanges allowing U.S. customers are more likely to default, with the odds of default increasing by approximately $e^{0.41975} \approx 1.521$, or 52.1%. In the probit model in Table 5, the coefficient is 0.2182. This implies an increase in the latent variable associated with default. Using the standard normal probability density function (PDF), the marginal effect suggests that allowing U.S. customers increases the probability of default by approximately 8.7%, assuming other variables are at their means. This result is statistically significant in the logit model but only marginally significant in the probit model. The *Transparency* variable, representing the transparency index of the exchange's home country, has a coefficient of 0.01489 in the logit model, meaning that higher transparency is associated with a slight increase in the odds of default. Specifically, for every 1-unit increase in the transparency index, the odds of default increase by $e^{0.01489} \approx 1.015$, or 1.5%. This variable is statistically significant in both models.

The *Affiliation* variable, which represents whether an exchange has an affiliation program, has a coefficient of -1.7 in the logit model results in Table 4, suggesting that having an affiliation program decreases the odds of default. Specifically, the odds of default decrease by approximately $e^{-1.7} \approx 0.183$, or 81.7%. In the probit model in Table 5, the coefficient for *Affiliation* is -1.69. This implies that having an affiliation program reduces the latent variable associated with default, which translates to a significant reduction in the probability of default. Using the standard normal PDF, the marginal effect suggests a decrease in the probability of default by approximately 9.1%, assuming other variables are at their means. However, this variable is only marginally significant at the 10% level in both models, indicating that while there is evidence of default risk mitigation due to affiliation programs, the relationship is weak and should be interpreted with caution.

To address the reverse causality concern, we recognize that it is possible for more stringent regulatory environments to lead to higher detection of risks or vulnerabilities, which may then reflect higher rates of exchange default in more regulated regions. In light of this, we conduct additional analyses to explore whether institutional settings (for example, Europe+U.S. vs. Rest-of-the-world, and developed vs. developing countries) reveal significant differences in the operational stability of cryptocurrency exchanges. For the Europe+U.S. dummy, the proportion of exchanges with high-running status in Europe+U.S. is 0.417 (10 out of 24), compared to 0.562 (18 out of 32) in the Rest-of-the-world. The pooled proportion is 0.5, and the calculated test statistic is approximately -1.41, with a *p*-value of 0.16. Similarly, for default proportions, the Europe+U.S. proportion is 0.333 (8 out of 24), while the Rest-of-the-world proportion is 0.406 (13 out of 32), with a pooled proportion of 0.375. The test statistic is approximately -0.65, with a *p*-value of 0.52. For the developed dummy, the running proportion in developed countries is also 0.417, while for developing countries it is 0.562, resulting in a *p*-value of 0.16. The default proportions for developed and developing countries are 0.333 and 0.406, respectively, with a *p*-value of 0.52. The proportions of high-running and high-default values are not significantly different between Europe+U.S. and the Rest-of-the-world, nor between developed and developing countries. These results suggest that institutional settings, such as regional or developmental status, do not significantly influence the observed patterns of exchange default or operational stability. Thus, concerns about reverse causality are reduced, as the lack of significant differences across regions and institutional settings indicates that additional factors contribute to the default likelihood of cryptocurrency exchanges.

The correlation matrix in Table A.2 and variance inflation factors (VIF) in Table A.3 indicate potential multicollinearity issues in the dataset, particularly concerning the variables *Certification* and *Ratings*, which exhibit VIFs of approximately 4.6 and 4.9, respectively. Nevertheless, since these VIF values are below the critical threshold of 5, they suggest moderate multicollinearity that could marginally inflate the standard errors of the regression coefficients. Machine learning models, such as random forest, are used in this study to address concerns about multicollinearity and potential endogeneity, providing further robustness checks for the model.

4.4. Causes of cryptocurrency exchange defaults: A subsample analysis

The data shows that 65.21% of all exchanges allow U.S. clients, but a higher proportion of these exchanges, 70.14%, have defaulted compared to only 61.38% of those that are still running. This suggests that exchanges catering to U.S. clients are more likely to default, potentially due to stringent U.S. regulatory requirements. Additionally, the average transparency index for defaulted exchanges is 59.94, slightly lower than the 61.30 observed for running exchanges; however, no significant mean difference is found between these two groups. This implies that transparency alone does not account for the differences in default rates. To further investigate the factors influencing the causes of cryptocurrency exchange defaults, a subsample analysis is conducted by implementing the following logistic regression:

$$\begin{aligned}\log\left(\frac{P(Y_i=1)}{1-P(Y_i=1)}\right) &= \beta_0 + \beta_1\text{U.S.\_allow} + \beta_2\text{DEX} + \beta_3\log(\text{No\_cryptos}) + \beta_4\text{Taker\_rate}+ \\ \beta_5\text{Maker\_rate} + \beta_6\text{Withdrawal\_fee} &+ \beta_7\text{Wire} + \beta_8\text{Credit} + \beta_9\text{Affiliation} + \beta_{10}\text{Certification}+ \\ &\beta_{11}\text{Ratings} + \beta_{12}\text{BBounty} + \beta_{13}\text{Transparency} + \beta_{14}\text{Control\_Age}\end{aligned} \tag{4}$$

where Y_i represents one of the following outcome variables: *Business*, *Hacked*, *MIA*, *Rebranding*, *Regulatory*, or *Scam*. $P(Y_i = 1)$ is the probability of the event occurring for each outcome variable.

$$P(Y_i = 1) = \sigma(Z) = \frac{1}{1+e^{-Z}} \tag{5}$$

where Z is the linear combination of the independent variables as defined above, and $\sigma(Z)$ is the logistic (or sigmoid) function that converts Z into a probability value.

The logistic regression results in Table 6 indicate that the predictors of default vary across these categories. Notably, "U.S._allow" and "Transparency", which are significant in the overall model, are not consistent predictors of defaults across all categories. For example, "U.S._allow" is significant only in the "Scam" category, while "Transparency" shows marginal significance in the same category. These findings suggest that the regulatory environment may influence the likelihood of certain types of defaults, such as scams, more than others, like disappearances (MIA). This aligns with the argument that countries with high transparency indices – typically developed nations – are more likely to experience higher levels of cryptocurrency scams. The availability of robust financial

Table 6
Subsample analysis: Factors affecting the cause of defaults.

	Dependent variable:					
	Business (1)	Hacked (2)	MIA (3)	Rebranding (4)	Regulatory (5)	Scam (6)
U.S._allow	0.401	0.050	−0.076	−0.414	−0.407	0.426
	(1.33)	(0.09)	(−0.31)	(−1.18)	(−0.96)	(0.88)
DEX	0.443	−16.294	−0.589	0.590	0.040	−0.160
	(1.11)	(−0.01)	(−1.58)	(1.2)	(0.05)	(−0.2)
No_cryptos	0.040	0.042	−0.091	−0.080	0.047	0.250
	(0.38)	(0.19)	(−0.98)	(−0.6)	(0.28)	(1.35)
Taker_rate	18.281	−2.795	−6.909	−19.068	−21.117	−181.820
	(1.18)	(−0.06)	(−0.46)	(−0.46)	(−0.46)	(−1.06)
Maker_rate	−17.731	0.093	8.834	27.692	−1.761	−21.850
	(−0.89)	(0.000)	(0.51)	(0.65)	(−0.04)	(−0.31)
Withdrawal_fee	0.007	0.010	−0.007	−0.024	0.008	0.007
	(0.96)	(0.91)	(−1.06)	(−1.53)	(0.69)	(0.68)
Wire	0.012	0.462	−0.629**	0.102	0.931**	0.896*
	(0.04)	(0.78)	(−2.52)	(0.28)	(1.98)	(1.91)
Credit	−0.184	−0.659	0.680**	−0.383	−0.808	−0.248
	(−0.57)	(−0.94)	(2.45)	(−0.88)	(−1.45)	(0.49)
Affiliation	−0.251	0.974	−0.555	0.928**	−0.828	0.383
	(−0.57)	(1.44)	(−1.44)	(2.00)	(−1.05)	(0.65)
Certification	12.358	−16.346	0.029	16.113	0.891	−1.585
	(0.01)	(0.00)	(0.01)	(0.02)	(0.41)	(−0.58)
Ratings	−13.512	−0.450	−0.358	−15.248	0.574	1.572
	(−0.01)	(0.00)	(−0.22)	(−0.01)	(0.33)	(0.90)
BBounty	0.728	0.888	0.536	1.088	−16.168	1.209
	(0.00)	(0.00)	(0.19)	(0.00)	(−0.01)	(0.45)
Transparency	0.0004	0.006	−0.006	−0.006	0.006	0.022*
	(0.06)	(0.39)	(−0.95)	(−0.70)	(0.52)	(1.77)
Control_Age	0.083	−0.009	−0.100	0.072	0.170*	−0.224*
	(1.21)	(−0.06)	(−1.62)	(0.83)	(1.67)	(−1.67)
Constant	−1.914***	−3.864***	1.022*	−1.296*	−3.605***	−4.428***
	(−3.07)	(−3.01)	(1.94)	(1.76)	(−3.53)	(−3.9)
Observations	366	366	366	366	366	366
Log likelihood	−192.380	−57.391	−239.540	−130.340	−91.147	−88.938
Akaike Inf. Crit.	414.760	144.780	509.080	290.690	212.290	207.880

Note: This table presents the subsample analysis of default cryptocurrency exchanges. Models (1) to (6) use different specific causes of default as dependent variables. For each cause of defaults, a dummy variable is assigned a value of 1 if the exchange is affected by that cause and 0 otherwise. Logistic regression is then applied for each case. The data spans from 2010 to February 2023. The logit model equation is given as:

$$\log\left(\frac{P(Y_i=1)}{1-P(Y_i=1)}\right) = \beta_0 + \beta_1 \text{U.S.\_allow} + \beta_2 \text{DEX} + \beta_3 \log(\text{No\_cryptos}) + \beta_4 \text{Taker\_rate} + \beta_5 \text{Maker\_rate} + \beta_6 \text{Withdrawal\_fee} + \beta_7 \text{Wire} + \beta_8 \text{Credit} + \beta_9 \text{Affiliation} + \beta_{10} \text{Certification} + \beta_{11} \text{Ratings} + \beta_{12} \text{BBounty} + \beta_{13} \text{Transparency} + \beta_{14} \text{Control\_Age}.$$

$P(Y_i = 1) = \sigma(Z) = \frac{1}{1+e^{-Z}}$, where Z is the linear combination of the independent variables as defined above, and $\sigma(Z)$ is the logistic (or sigmoid) function that converts Z into a probability value. Where Y_i represents one of the following outcome variables: *Business*, *Hacked*, *MIA (missing in action)*, *Rebranding*, *Regulatory*, or *Scam*. $P(Y_i = 1)$ is the probability of the event occurring for each outcome variable. The variables include U.S. user allowance (U.S._allow), the number of listed cryptocurrencies (No_cryptos), taker fees (Taker_rate), maker fees (Maker_rate), withdrawal fees (Withdrawal_fee), and ratings (Ratings). Binary variables include decentralized exchange status (DEX), certification status (Certification), support for wire transfers (Wire), credit card payments (Credit), affiliation programs (Affiliation), and bug bounty programs (BBounty). The transparency index of the home country is represented by (Transparency). Control_Age refers to the age of the exchange in years as the control variable for survivorship bias.
Z-value reported in parentheses.
Signif. codes: '***' 0.01 '**' 0.05 '*' 0.1.

infrastructure, trust in regulatory oversight, and greater accessibility to online financial services in these countries create fertile ground for both legitimate and fraudulent activities. The significance of "U.S._allow" in the "Scam" category suggests that permissive regulatory environments, which facilitate the growth of blockchain technologies, also open the door for criminal exploitation. Similarly, the marginal significance of "Transparency" in this category suggests that greater transparency, while beneficial for governance, does not fully mitigate scam risks in the crypto space. In contrast, countries with lower transparency indices often lack the infrastructure and regulatory frameworks to support widespread cryptocurrency adoption. As a result, they experience fewer scams primarily due to lower levels of crypto usage. However, as these countries develop and potentially adopt more transparent systems, they may face similar challenges in balancing technological innovation with the need for stringent regulatory oversight to prevent fraud. Thus, the logistic regression results underscore the complexity of the relationship between transparency, regulatory environments, and the prevalence of crypto-related scams.

4.5. Robustness check

To assess the robustness of the analysis and address the potential multicollinearity issue, different machine learning algorithms are implemented. In addition to random forest and support vector machine (SVM) algorithms, various alternative methodologies are employed. These machine learning approaches are known for their ability to handle multicollinearity-related problems effectively. As highlighted in Table A.2 in the Appendix, there is a strong correlation between the *Ratings* and the *Certification* as well as the *Taker* and *Marker* rate. By incorporating random forest, which is an ensemble learning method, the analysis benefits from the model's ability to capture complex interactions and nonlinear relationships among variables. This is particularly valuable when dealing with multicollinearity, as the algorithm can handle correlated predictors without compromising performance. Random forest achieves this by randomly selecting subsets of features during training and making predictions based on a collection of decision trees. In addition to random forest, SVM is utilized to further mitigate the multicollinearity issue. SVM is a powerful algorithm that excels in handling high-dimensional data and can effectively handle multicollinearity problems through its unique approach to finding the optimal hyperplane that maximizes the margin between different classes. By employing SVM, the analysis accounts for the interdependencies among variables while still maintaining accurate predictions. By combining these two robust machine learning techniques, the analysis ensures a comprehensive examination of the data, considering both the complex interactions and potential multicollinearity among variables. This approach enhances the reliability and robustness of the results, providing a more accurate assessment of the predictors' influence on the target variable.

4.5.1. Random forest

The confusion matrix in Table A.7 in the Appendix indicates that the accuracy of the random forest model depends on the optimal combination of training and test data. Notably, the overall accuracy of the random forest model is significantly higher than that of the logit and probit models. However, with a 90% training and 10% test data split, the prediction power appears to decrease due to a higher Type II error.

Table 7
Prediction accuracy of default cryptocurrency exchanges using random forest.

Metric	Training proportions:			
	60%	70%	80%	90%
Accuracy	0.928	0.952	0.988	0.819
95% confidence interval	(0.849, 0.973)	(0.881, 0.987)	(0.935, 1.000)	(0.720, 0.895)
No information rate	0.566	0.566	0.566	0.566
Kappa	0.853	0.902	0.975	0.626
McNemar's test P-value	1.000	1.000	1.000	0.302
Sensitivity	0.917	0.944	0.972	0.722
Specificity	0.936	0.957	1.000	0.894
Pos prediction value	0.917	0.944	1.000	0.839
Neg prediction value	0.936	0.957	0.979	0.808
Prevalence	0.434	0.434	0.434	0.434
Detection rate	0.398	0.410	0.422	0.313
Detection prevalence	0.434	0.434	0.422	0.373
Balanced accuracy	0.926	0.951	0.986	0.808
Positive class	1	1	1	1

Note: This table presents the prediction accuracy metrics for default cryptocurrency exchanges using the random forest model, with training data proportions ranging from 60% to 90%. Metrics reported include accuracy, confidence intervals, and model performance measures such as sensitivity and specificity. 'No Information Rate' reflects the probability of the most common outcome. 'Kappa' indicates agreement beyond chance. 'McNemar's Test' checks for significant differences between predictions and actual values. R package `randomForest` is used to run the random forest prediction model. Detailed calculation methods for each metric can be found in Table A.6 in the Appendix.

Table 7 presents the prediction accuracy of default cryptocurrency exchanges using the random forest model at different training data proportions, and it reveals some notable findings. The accuracy values at different training data percentages suggest that as the amount of training data increases, the model's performance generally improves. Notably, the accuracy decreases significantly when using 90% of the training data, dropping to 0.819, which raises concerns about the model's reliability in accurately predicting default cryptocurrency exchanges. The 95% confidence intervals provide a range of possible accuracy values, indicating the uncertainty associated with the predictions. In some cases, such as the 80% training data, the confidence interval (0.935, 1.000) suggests a high level of confidence in the accuracy estimates. In contrast, for the 60% training data, the confidence interval (0.849, 0.973) is relatively wide, indicating a higher degree of uncertainty in the accuracy estimate. Comparing the model's performance against the 'No Information Rate' reveals that the random forest model consistently outperforms a naive model that predicts the majority class for all instances. This suggests that the model captures some meaningful patterns in the data and provides predictive value beyond random chance. The 'Kappa' coefficient, which measures the agreement between predicted and actual classes, corrected for chance, indicates a moderate to substantial agreement between the model's predictions and the actual classes. The higher values, such as 0.975 for 80% training data, imply a strong agreement and better overall performance of the model. Examining the sensitivity (true positive rate, which measures the proportion of actual positives correctly identified) and specificity (true negative rate, which measures the proportion of actual negatives correctly identified) values, it can be observed that the model generally performs well

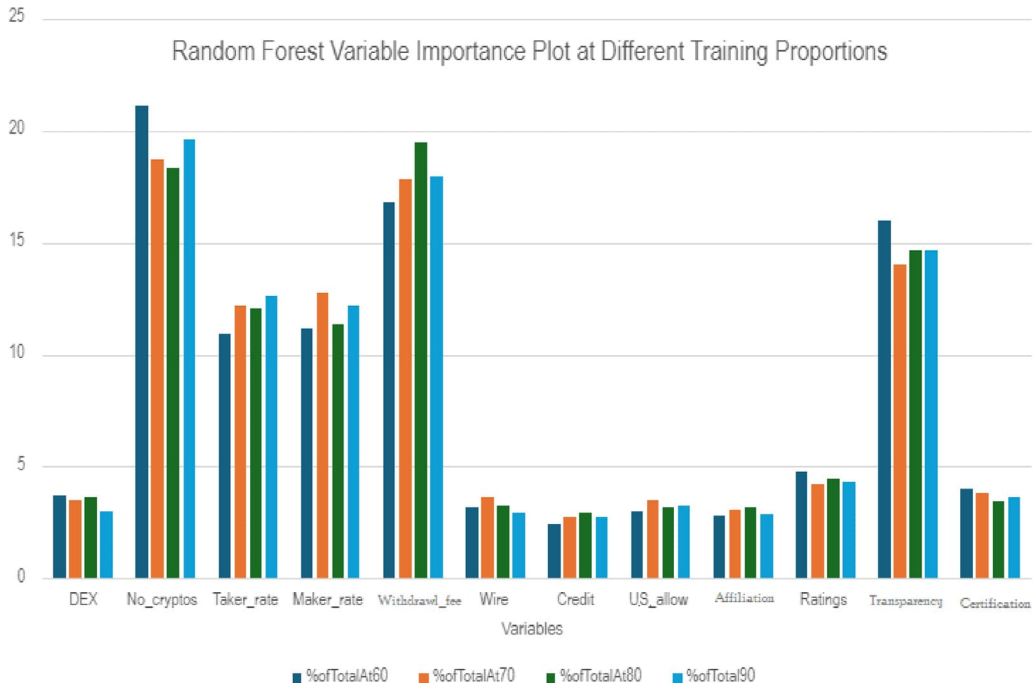

Fig. 6. Variable importance plot of random forest model at different training proportions. **Note**: The variables include U.S. user allowance (U.S._allow), the number of listed cryptocurrencies (No_cryptos), taker fees (Taker_rate), maker fees (Maker_rate), withdrawal fees (Withdrawal_fee), and ratings (Ratings). Binary variables include decentralized exchange status (DEX), certification status (Certification), support for wire transfers (Wire), credit card payments (Credit), affiliation programs (Affiliation), and bug bounty programs (BBounty). The transparency index of the home country is represented by (Transparency). Percentage of total values are given in Table A.8 in the Appendix.

in correctly identifying both positive and negative instances. However, the sensitivity drops noticeably for the 90% training data, indicating that the model struggles to identify default cryptocurrency exchanges correctly in that scenario. The positive and negative prediction values provide insights into the model's precision in predicting the respective classes. For the 80% training data, the model achieves a perfect positive prediction value, reflecting a strong confidence in identifying default cryptocurrency exchanges. In contrast, the negative prediction value decreases for the same training data, indicating a higher likelihood of false negatives. The balanced accuracy, which is the average of sensitivity and specificity, provides an overall measure of the model's performance by considering both sensitivity and specificity. While the values are generally high, reaching 0.986 for 80% training proportion, the drop in balanced accuracy for the 90% training data indicates a trade-off between correctly identifying positive and negative instances. The random forest model shows promise in predicting default cryptocurrency exchanges, but its performance is sensitive to the amount of training data used. Nevertheless, the overall accuracy, sensitivity, detection rate, and balanced accuracy suggest that the default prediction model is robust. Moreover, the random forest is also able to correctly predict the running cryptocurrency exchanges with high accuracy.[5]

The variable importance plot of the random forest model in Fig. 6 reveals that the learning process is not uniform across all variables using the training data. Additionally, as the proportion of the training dataset increases, certain variables such as the number of cryptocurrencies, withdrawal fees, and the transparency index demonstrate enhanced learning capabilities. This suggests that a larger training dataset allows the model to better understand the relationship between these variables and the probability of crypto exchange bankruptcy. These findings emphasize the importance of considering factors such as the variety of cryptocurrencies offered, withdrawal fees imposed, and the level of corruption where the exchange is located when assessing their financial stability.

It is important to note that the other remaining factors related to cryptocurrency exchanges do not exhibit significant improvements in their learning patterns as the training data proportion increases. This suggests that these variables might have a limited impact or provide less reliable insights into predicting defaults among cryptocurrency exchanges. Further exploration and analysis are required to better understand the dynamics of these factors and their influence on exchange failures.

4.5.2. Support vector machine

To check the robustness of the machine learning models, this study implements another popular approach of binomial classification model known as the support vector machine (SVM).[6] If the class labels are 1 and 0, and a linear kernel is used with

[5] Please, see Table A.10 in the Appendix.

[6] R package `e1071` is used to run the support vector machine prediction model.

the SVM model, then the SVM model equation becomes:

$$\begin{aligned} p = sign(\sum LM_i(2p_i - 1)(\beta_{i,1}\text{DEX} + \beta_{i,2}\log(\text{No\_cryptos}) + \beta_{i,3}\text{Taker\_rate}+ \\ \beta_{i,4}\text{Maker\_rate} + \beta_{i,5}\text{Withdrawal\_fee} + \beta_{i,6}\text{Wire} + \beta_{i,7}\text{Credit} + \beta_{i,8}\text{U.S.\_allow}+ \\ \beta_{i,9}\text{Affiliation} + \beta_{i,10}\text{Ratings} + \beta_{i,11}\text{Transparency} + \beta_{i,12}\text{Certification}+ \\ \beta_{13}\text{Control\_Age}) + \epsilon) \end{aligned} \tag{6}$$

where $\beta_{(i,1)}, \beta_{(i,2)}, \dots, \beta_{(i,13)}$ are the feature vectors for the ith training instance and the instance to be predicted, respectively. p_i is the class label (1 or 0) for the ith training instance, $(LM)_i$ is the Lagrange multiplier for the ith training instance, and ϵ is the bias term.

The goal of training the SVM model is to find the optimal values of the Lagrange multipliers $(LM)_i$ that maximize the margin between the decision boundary and the closest training instances (support vectors), subject to the constraint that the predicted labels match the true labels for the training instances. In the case of a linear kernel, the decision boundary is a hyperplane defined by:

$$\begin{aligned} \sum LM_i(2p_i - 1)(\beta_{i,1}\text{DEX} + \beta_{i,2}\log(\text{No\_cryptos}) + \beta_{i,3}\text{Taker\_rate}+ \\ \beta_{i,4}\text{Maker\_rate} + \beta_{i,5}\text{Withdrawal\_fee} + \beta_{i,6}\text{Wire} + \beta_{i,7}\text{Credit} + \beta_{i,8}\text{U.S.\_allow}+ \\ \beta_{i,9}\text{Affiliation} + \beta_{i,10}\text{Ratings} + \beta_{i,11}\text{Transparency} + \beta_{i,12}\text{Certification}+ \\ \beta_{13}\text{Control\_Age}) + \epsilon = 0 \end{aligned} \tag{7}$$

The SVM model predicts the positive class (1) if $p > 0$ and the negative class (0) otherwise.

Table A.9 in the Appendix presents the confusion matrix for a binary classification problem using the SVM to predict the status of cryptocurrency exchanges. At 60% training data, the SVM model correctly predicts 112 instances in the Default group (actual Default group) while misclassifying 39 instances from the Default group as part of the Running group (predicted Running group). Similarly, it correctly predicts 168 instances in the Running group (actual Running group) while misclassifying 19 instances from the Running group as part of the Default group. The same pattern of predicted and actual group counts is presented for the SVM model at different percentages of training data: 70%, 80%, and 90%. The table allows for an evaluation of the SVM model's performance by comparing the predicted and actual groups, observing the number of correct classifications and misclassifications for each group. By analyzing the table, the accuracy of the SVM model in predicting the status of cryptocurrency exchanges based on the given exchange characteristics can be assessed.

Table 8
Prediction accuracy of default cryptocurrency exchanges using support vector machine.

Metric	Training proportions:			
	60%	70%	80%	90%
Accuracy	0.828	0.819	0.799	0.788
Accuracy (95% CI)	(0.784, 0.867)	(0.766, 0.864)	(0.730, 0.856)	(0.686, 0.869)
Precision (Class 1)	0.812	0.807	0.798	0.755
Precision (Class 0)	0.855	0.835	0.800	0.833
Recall (Class 1)	0.898	0.867	0.833	0.860
Recall (Class 0)	0.742	0.765	0.759	0.714
F1-Score (Class 1)	0.853	0.836	0.815	0.804
F1-Score (Class 0)	0.794	0.798	0.779	0.769

Note: This table reports the prediction accuracy of default cryptocurrency exchanges using the support vector machine model at different training data percentages. "Class 1" and "Class 0" refer to the positive (Default) and negative (Running) classes, respectively. R package `e1071` is used to run the support vector machine prediction model. Please check Table A.6 in the Appendix for details on how different accuracy measures are calculated.

Table 8 provides a critical analysis of the prediction accuracy of the SVM model for default cryptocurrency exchanges, considering different percentages of training data. The 'Metric' column indicates the prediction threshold utilized by the SVM model, while "Class 1" and "Class 0" represent the positive (Default) and negative (Running) classes, respectively. The accuracy values reported in the table demonstrate the overall correctness of the SVM model's predictions. At 60% training data, the model achieves an accuracy of 0.828, indicating that approximately 82.8% of the predictions are correct. However, as the percentage of training data increases, the accuracy gradually decreases, reaching 0.788 at 90% training data. These accuracy values measure the model's ability to correctly classify instances into their respective classes. To gain a deeper understanding of the model's performance, precision (the proportion of positive identifications that are actually correct), recall (the proportion of actual positives that are correctly identified), and F1-scores (the harmonic mean of precision and recall, providing a balance between the two) are also presented for both Class 1 (Default) and Class 0 (Running). Analyzing the precision values, we observe that the SVM model achieves relatively high precision for Class 1, ranging from 0.755 to 0.812 across different percentages of training data. This indicates that when the model predicts an instance to be in the Default class, it is generally accurate. Similarly, the precision values for Class 0 range from 0.8 to 0.855, indicating reasonably accurate predictions for the Running class. The recall values, on the other hand, provide insights into the SVM model's ability to identify instances from each class correctly. The recall values for Class 1 range from 0.833 to 0.898, indicating that the model effectively captures a substantial portion of the actual Default instances. For Class 0, the recall values range from 0.714 to 0.765, suggesting a relatively lower ability to correctly identify Running instances. The F1-scores provide a combined assessment of precision and recall, highlighting the overall performance of the SVM model. The F1-scores for Class 1 range from 0.804 to 0.853, while for Class 0, they range from 0.769 to 0.798. These values indicate a reasonable balance between precision and recall for both classes. Overall, the SVM model demonstrates moderate to good prediction accuracy for running cryptocurrency exchanges, with accuracy values ranging from 0.788 to 0.828. While the model shows relatively high precision for Class 1 and reasonable precision for Class 0, it exhibits slightly lower recall for Class 0. The F1-scores highlight a balanced performance of the model, considering both precision and recall for both classes.

The SVM model demonstrates consistent performance in identifying default cryptocurrency exchanges, particularly in terms of sensitivity, which indicates the model effectively captures most of the actual defaults. The precision for default predictions shows that when the model classifies an exchange as likely to default, it tends to be accurate. For running exchanges, while the precision is reasonable, the model exhibits a slightly lower ability to correctly identify all running instances. The F1-scores, which balance precision and recall, highlight reliable overall performance for predicting both default and running cryptocurrency exchanges, reflecting the robustness of the model in handling both classes effectively.

A comparison of the accuracy of SVM and random forest reveals that these machine learning algorithms do not always outperform conventional statistical models like the logit and probit models. Despite implementing various training and testing proportions, the SVM model does not demonstrate superior performance compared to the logit and probit models. Additionally, at higher training proportions, the predictive power of the random forest model significantly diminishes. Nevertheless, the proposed model in this study for predicting cryptocurrency exchange defaults demonstrates a high level of accuracy and robustness across both conventional statistical approaches and advanced machine learning techniques.

The differences in the behavior of random forest and SVM stem from several key distinctions between these two algorithms. (i) Random forest is an ensemble learning method that creates multiple decision trees and combines their predictions to produce a final output. In contrast, SVM is a linear classifier that identifies the optimal boundary between classes in a high-dimensional feature space. (ii) Random forest is relatively simple to implement and interpret, whereas SVM can be more complex, particularly when addressing non-linear classification problems. (iii) Random forest has limitations in feature selection since it generates many decision trees, each using different subsets of features. SVM, however, can aid in feature selection by identifying the most important features based on their coefficients in the decision boundary. (iv) Random forest handles non-linear data effectively due to the flexibility of decision trees, whereas SVM is primarily designed for linear classification but can manage non-linear problems using kernel functions. (v) Random forest can be computationally expensive, particularly when the number of trees is large, while SVM is computationally efficient but may become slower with large datasets or high-dimensional feature spaces. In conclusion, both random forest and SVM have distinct strengths and weaknesses. The choice between them depends on the specific requirements of the problem, such as the nature of the data, interpretability needs, and computational constraints.

4.5.3. Comparing random forest and SVM with other machine learning models

In this study, various other machine learning tools are also explored. Popular techniques like extreme gradient boosting (XGBoost) demonstrate significant overfitting, particularly with a relatively small sample size of 845.[7] Across various training proportions, XGBoost achieves 100% accuracy, suggesting a serious memorization issue rather than true model generalization. While techniques such as regularization can introduce randomness into training, similar effects can also be achieved using other machine learning tools, such as random forest techniques (Nielsen, 2016). Moreover, complex models like XGBoost are generally more suitable for larger sample sizes. In this context, McNamara et al. (2022) find that XGBoost shows severe overfitting with sample sizes ranging from 100 to 1000 but begins to perform comparably to random forest when the sample size increases to between 1000 and 2000.

Table 9
Prediction accuracy of default cryptocurrency exchanges using different machine learning models.

Model/Hyperparameters	Training proportions%: Mean Accuracy (95% Confidence Interval)			
	60%	70%	80%	90%
Random forest ntree = 500, mtry = 5	0.928 (0.849–0.973)	0.952 (0.881–0.987)	0.988 (0.935–1.000)	0.819 (0.720–0.895)
Support vector machine type = C-classification, kernel = linear	0.828 (0.784–0.867)	0.819 (0.766–0.864)	0.799 (0.730–0.856)	0.788 (0.686–0.869)
Gradient boosting machine n.trees = 5000, interaction.depth = 3, shrinkage = 0.01	0.825 (0.781–0.864)	0.826 (0.771–0.871)	0.822 (0.756–0.877)	0.821 (0.723–0.896)
Neural networks hidden.layers = 5, linear.output = False	0.774 (0.726–0.818)	0.738 (0.679–0.791)	0.780 (0.709–0.840)	0.795 (0.692–0.876)
Naive Bayes default	0.629 (0.575–0.680)	0.619 (0.556–0.679)	0.613 (0.535–0.687)	0.590 (0.477–0.697)

Note: This table presents the mean prediction accuracy and accuracy at the 95% confidence interval for different machine learning models applied to cryptocurrency exchanges at varying training data percentages, along with the model hyperparameters.

Table 9 shows the comparative performance accuracy of various machine learning models across different training proportions. It summarizes the prediction accuracy of default cryptocurrency exchanges using various machine learning models—random forest, SVM, gradient boosting machine (GBM), neural networks, and naive Bayes.[8] The table reports the hyper-parameters, mean accuracy and the 95% confidence interval (CI) for each model. Among the models, random forest achieves the highest mean accuracy at

[7] R-package `xgboost` is implemented to run the XGBoost model.

[8] R-packages `gbm` `neuralnet`, and `e1071` are implemented to run the GBM, neural network and naive Bayes models.

lower training proportions (98.8% at 80% training data), with relatively narrow confidence intervals, indicating robust performance. However, its accuracy drops significantly to 81.9% at 90% training data, which might suggest overfitting when more data is used for training. On the other hand, SVM maintains fairly consistent performance across different training proportions and shows more stable results without significant drops in accuracy. Based on these results, random forest and SVM appear to be the best options for making predictions in this context. Random forest achieves the highest mean accuracy at most training proportions, making it a strong choice for models requiring high precision. Despite its lower mean accuracy compared to random forest, SVM demonstrates more consistent performance and less variability across different training data proportions, which is desirable for generalizability and robustness in real-world applications. The combination of random forest's high accuracy and SVM's stability makes these two models the most reliable choices for predicting the default of cryptocurrency exchanges, providing a balance between accuracy and robustness across various training scenarios.

Random forest and SVM offer unique advantages over many machine learning models due to their approaches to data handling and overfitting. Random forest is an ensemble method that combines multiple decision trees to reduce variance and improve accuracy, making it highly effective in resisting overfitting, especially on small or moderately sized datasets. This ensemble approach offers more flexibility than models like XGBoost, which, despite achieving high accuracy, often risks overfitting due to its strong reliance on boosting iterations. In contrast, SVM excels by optimizing a hyperplane that maximizes the margin between classes, allowing it to perform consistently across various training sizes and making it highly generalizable when data is more variable.

In practice, random forest is particularly valuable when high accuracy is needed, as it can capture complex patterns by leveraging multiple trees, making it suitable for applications requiring precision. The strength of SVM lies in its stability and resilience to data fluctuations, making it preferable when model consistency is essential. While simpler models like naive Bayes may work efficiently on independent or text-based data, random forest and SVM are better suited for complex, structured data with interdependent features, as they can effectively capture these intricate relationships. Thus, random forest is advantageous in cases prioritizing accuracy, while the reliability of SVM makes it suitable for applications that demand robustness in real-world, diverse data contexts.

The naive Bayes classifier has the lowest accuracy in this study as it operates under the assumption that all features are conditionally independent given the class label. This means the model treats each feature separately when calculating the probability of a particular class. For a new instance, it computes the probability of that instance belonging to each class by independently considering the contribution of each feature, then classifies the instance into the class with the highest posterior probability. In contrast, the SVM algorithm works by finding the hyperplane that best separates the classes in the feature space. SVM takes all features into account simultaneously and identifies the hyperplane that maximizes the margin. This suggests that, for classifying between running and default cryptocurrency exchanges, combining the features provides better classification performance than treating each feature independently, as shown in the comparison by Ma et al. (2020). Furthermore, naive Bayes can struggle with more complex datasets where the relationships between features are significant and cannot be captured by the independence assumption. Other algorithms, such as random forest, SVM, and neural networks, often achieve higher accuracy by capturing these complex relationships in the data. However, naive Bayes remains particularly effective when dealing with large-scale text data, as highlighted by Chen et al. (2009) and Ting et al. (2011).

4.5.4. Stacked ensemble model

To enhance predictive performance, all machine learning models used in this study – random forest, SVM, GBM, neural networks, and naive Bayes – are combined into a single meta-model. This approach, known as a stacked ensemble model (SEM), leverages the strengths of each individual model to improve predictions. By integrating the outputs from all models, the SEM often achieves superior predictive accuracy compared to relying on any single model alone.

The SEM in this study heavily relies on the GBM algorithm, as evidenced by its consistently negative and statistically significant coefficients, as shown in Table 10. These results indicate a strong inverse relationship between GBM's predictions and the final ensemble output. In contrast, the other algorithms – random forest, SVM, neural networks, and naive Bayes – also display negative coefficients, but these are not statistically significant, suggesting that their contributions to the final model are minimal and not impactful.

The SVM model maintains consistent accuracy across various training proportions, with accuracy values ranging from 0.817 to 0.834 and 95% confidence intervals indicating stability (for example, 0.789–0.872 at 60% training). The AIC values range from 464.4 to 654.8, slightly increasing as the training proportion grows, which may indicate some trade-offs in model complexity. Despite incorporating multiple algorithms, the model's performance is primarily driven by GBM, while the contributions of the other algorithms are less significant, suggesting potential redundancy in the ensemble. Even though GBM is the major contributor to the ensemble's performance, the stacked model still offers a slight advantage by combining predictions from multiple models, leading to more robust and generalizable predictions across all training proportions except at 70%, as illustrated in Tables 9 and 10.

Unlike single models, which may struggle with specific data complexities or show inconsistent performance, SEM combines predictions from multiple algorithms, effectively balancing their unique strengths. This leads to more robust predictions, making SEM particularly valuable in high-stakes fields like finance, healthcare, and risk management, where small predictive improvements can have substantial impacts. By mitigating individual model weaknesses, SEM provides a level of adaptability that single models cannot achieve, making it ideal for applications where data is complex, noisy, or highly variable. Consequently, SEM empowers decision-makers with a more consistent and accurate predictive tool, better suited to handle real-world uncertainties than any single algorithm alone. However, SEM has certain limitations. Its layered structure and reliance on multiple models increase computational demands, which can be resource-intensive and less suitable for real-time applications. Additionally, combining multiple models

Table 10
Stacked ensemble model, algorithm significance.

Algorithm	Training proportions			
	60% Training	70% Training	80% Training	90% Training
Intercept	3.010***	2.886***	3.1835***	3.020***
	(8.17)	(10.37)	(9.22)	(10.27)
Random forest	−1.827	−0.832	−1.6591	−1.266
	(−1.28)	(−1.07)	(−1.27)	(−1.07)
Support vector machine (SVM)	−1.338	−0.624	−0.4258	−0.223
	(−1.30)	(−0.66)	(−0.51)	(−0.24)
Gradient boosting machine (GBM)	−2.913***	−4.350***	−3.2493***	−3.254***
	(−3.42)	(−4.76)	(−3.43)	(−4.47)
Neural networks	−0.143	0.340	−0.9161	−0.920
	(−0.19)	(0.39)	(−1.20)	(−1.12)
Naive Bayes	0.446	−0.520	−0.0654	−0.454
	(0.90)	(−1.26)	(−0.16)	(−1.23)
Null deviance	695.11 (507 df)	811.52 (592 df)	811.52 (592 df)	1042.66 (761 df)
Residual deviance	452.43 (502 df)	499.39 (587 df)	499.09 (587 df)	642.76 (756 df)
Akaike information criterion (AIC)	464.4	511.4	511.1	654.8
Number of Fisher Scoring iterations	4	5	5	5
Accuracy (Mean)	0.834	0.817	0.833	0.831
Accuracy (95% confidence interval)	(0.789–0.872)	(0.764–0.863)	(0.781–0.877)	(0.733–0.904)

Note: This table presents results from a stacked ensemble model predicting default cryptocurrency exchange classifications. The ensemble model combines five machine learning algorithms – random forest, support vector machine (SVM), gradient boosting machine (GBM), neural networks, and naive Bayes – using the `caretEnsemble` R package.
z-value in parentheses.
Signif. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.
(Dispersion parameter for binomial family taken to be 1).
df: degrees of freedom.

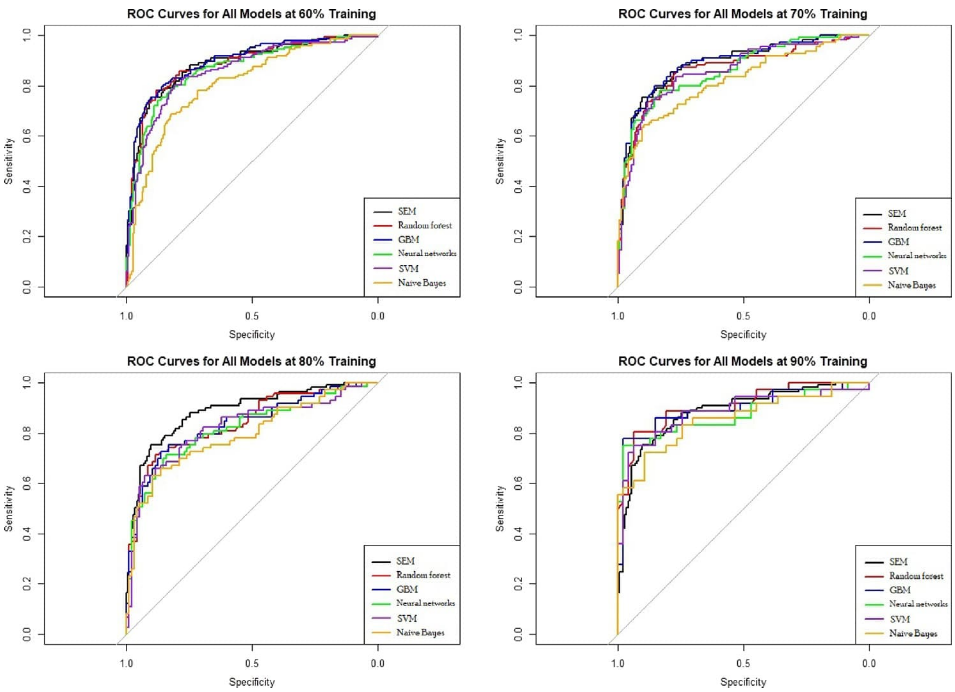

Fig. 7. Receiver operating characteristics curves of different machine learning models. **Note:** This graph is created using the `ggplot2` R package. The receiver operating characteristics (ROC) curves of the stacked ensemble model (SEM), random forest, gradient boosting machine (GBM), neural network, support vector machine (SVM), and naive Bayes are shown. The X-axis represents specificity (true negatives correctly identified), and the Y-axis represents sensitivity (true positives correctly identified) when predicting cryptocurrency exchange defaults across different training proportions.

makes SEM difficult to interpret, a drawback in fields that require transparency. In some cases, certain models may contribute minimally to the ensemble, leading to unnecessary complexity.

The receiver operating characteristics (ROC) curves for all models across different training proportions in Fig. 7 demonstrate the effectiveness of the SEM in classification tasks. The SEM consistently outperforms at 80% training proportions to individual models as indicated by the curves. The ROC of random forest, SVM, and GBM remain closest to the top-left corner across all other training proportions, reflecting their superior ability to balance sensitivity and specificity. This suggests that the ensemble approach effectively combines the strengths of each model, leading to more accurate predictions compared to using any single model on its own. Additionally, as the training proportion increases from 60% to 90%, there is a general trend of improved performance across all models, though the gains diminish slightly at higher training proportions. This indicates that while more data can enhance model accuracy, the marginal benefit of additional data decreases as models become more trained. Notably, the naive Bayes model consistently shows the weakest performance, with its ROC curve being furthest from the top-left corner in all scenarios. This aligns with the known limitations of naive Bayes, particularly its assumption of feature independence, which may not hold in complex datasets. The negative coefficients for GBM across all training proportions indicate that predictions made by GBM are inversely correlated with the final output of the SEM. In other words, when GBM assigns a higher probability or score to a particular class, the ensemble model tends to reduce the probability or score of that class in its final prediction. This inverse relationship suggests that the ensemble model is correcting or adjusting the GBM predictions, possibly because GBM is overfitting that the ensemble seeks to balance.

4.5.5. K-fold cross validation tests

There are various methods for evaluating the forecasting accuracy of a model. These include cross-validation, rolling window testing, extended window testing, and out-of-sample testing, among others. A key method in statistical modeling and machine learning is cross-validation, which aims to estimate the performance of the model precisely, evaluate its variability, avoid overfitting, and guide hyperparameter tuning. It provides a more accurate estimate of the model's ability to generalize to new data than a single train/test split by dividing the data into multiple subsets and training the model iteratively on various combinations of these subsets. This approach improves the assessment of the stability and robustness of the model by enabling the evaluation of both performance and variability across different data partitions.

Table 11
K-fold cross-validation results for logit and probit models.

Model	N	Predictors	Resampling method	Sample sizes
Logit model				
	845	13	5-Fold cross-validation	550, 550, 550, 550, 550
Performance	Accuracy: 0.8142 (95% CI: 0.7860–0.8423) Kappa: 0.6184			
Probit model				
	845	13	5-Fold cross-validation	550, 550, 550, 550, 550
Performance	Accuracy: 0.8067 (95% CI: 0.7935–0.8200) Kappa: 0.6023			

Note: This table reports the prediction accuracy of 5-fold cross-validation tests for logit and probit models in predicting cryptocurrency exchange defaults. The 13 'Predictors' for both logit and probit models include whether the exchange is decentralized DEX dummy (1/0), the number of cryptocurrencies listed (No_cryptos), fee rates (Taker_rate, Maker_rate), withdrawal fees (Withdrawal_fee), whether the exchange supports wire transfer Wire dummy (1/0) or credit card deposits Credit dummy (1/0), whether U.S. customers are allowed U.S._allow dummy (1/0), affiliation program presence (Affiliation dummy), certification status Certification dummy, transparency index of the home country (Transparency), and a control variable (Control_Age). 'Kappa' is a statistic that measures the agreement between predicted and observed classifications, adjusted for the possibility of agreement occurring by chance. The results are obtained using the `caret` R-package. The data is partitioned into 65% training and 35% validation for each fold. The cryptocurrency exchange data spans from 2010 to February 2023, 'N' representing 845 exchanges.

The performance of the logit and probit models in predicting cryptocurrency exchange defaults appears promising based on the k-fold cross-validation results, as shown in Table 11. The logit model demonstrated an accuracy of 78.70% (95% CI: 76.68%–80.73%), whereas the probit model exhibited a marginally higher accuracy of 79.05% (95% CI: 76.30%–82.53%). These findings suggest that both models perform relatively well in terms of prediction, with the probit model outperforming the logit model by a small margin in the 5-fold cross-validation tests. Although these results are slightly lower than the primary results reported in Table 4 for the logit model (81.18%, 95% CI: 78.38%–83.77%) and Table 5 for the probit model (81.42%, 95% CI: 78.63%–83.99%), the k-fold cross-validation results confirm the predictive accuracy of the models.

The k-fold cross-validation test results for the random forest and SVM models, as presented in Table 12, indicate promising performance in predicting cryptocurrency exchange defaults. The random forest model achieves an accuracy of 81.7% (95% CI: 78.1%–84.7%), with sensitivity and specificity values of 73.07% and 88.31%, respectively. Similarly, the SVM model demonstrates an accuracy of 80.47% (95% CI: 73.69%–86.16%), along with precision, recall, and F1-score values of 77.63%, 78.67%, and 78.15%, respectively. These findings suggest that both models perform reasonably well in predicting outcomes, with the random forest model achieving slightly higher accuracy than the SVM model. The resampling method used in the cross-validation involves 5-fold partitioning of the data into training (65%) and validation (35%) sets for each fold, ensuring robust evaluation of the models. Comparing model performance at different training and test proportions, the random forest prediction in Table 7 at 60% training

Table 12
K-fold cross-validation test results of random forest, support vector machine, and gradient boosting models.

Model	N	Predictors	Resampling method	Sample sizes
Random Forest	845	13	5-Fold cross-validation	541, 541, 541, 540, 541
Performance		Accuracy	0.817	95% CI (0.7810-0.8470)
		Sensitivity	0.7307	
		Specificity	0.8831	
Support vector machine	845	13	5-Fold cross-validation	541, 541, 541, 540, 541
Performance		Accuracy	0.8047	95% CI (0.7369-0.8616)
		Precision	0.7763	
		Recall	0.7867	
		F1-Score	0.7815	
Gradient boosting machine	845	13	5-Fold cross-validation	550, 550, 550, 550, 550
Performance		Accuracy	0.7890	95% CI (0.7754-0.8655)
		Kappa	0.5661	

Note: This table reports the prediction accuracy of 5-fold cross-validation tests for the random forest, support vector machine, and gradient boosting models. The results are obtained by implementing the *caret* R-package. The data is partitioned into 65% training and 35% validation for each fold. The 13 'Predictors' for all three models include whether the exchange is decentralized DEX dummy (1/0), the number of cryptocurrencies listed (No_cryptos), fee rates (Taker_rate, Maker_rate), withdrawal fees (Withdrawal_fee), whether the exchange supports wire transfer Wire dummy (1/0) or credit card deposits Credit dummy (1/0), whether U.S. customers are allowed U.S._allow dummy (1/0), affiliation program presence (Affiliation dummy), certification status Certification dummy, transparency index of the home country (Transparency), and a control variable (Control_Age). 'Kappa' is a statistic that measures the agreement between predicted and observed classifications, adjusted for the possibility of agreement occurring by chance. Additionally, the performance metrics include Sensitivity (True Positive Rate), which measures the proportion of actual positives correctly identified; Specificity (True Negative Rate), which measures the proportion of actual negatives correctly identified; Precision, which measures the proportion of positive predictions that are actually correct; Recall, which measures the proportion of actual positives that are correctly identified; and F1-Score, which is the harmonic mean of Precision and Recall. The cryptocurrency exchange data spans from 2010 to February 2023, 'N' representing 845 exchanges.

shows an accuracy of 92.8%, whereas the SVM in Table 8 shows an accuracy of 82.8%. Although the random forest prediction in the k-fold cross-validation test is 12% lower, it aligns closely with the prediction at the 90% training level. This consistency indicates that the model performs well across different subsets of the data, providing a high level of confidence in its predictive estimation.

K-fold cross-validation highlights why random forest and SVM are the top choices for predicting cryptocurrency exchange defaults. Although GBM shows superior performance compared to SVM in Table 9, cross-validation indicates that SVM remains the better option. However, GBM can still be included alongside SVM in SEM models to enhance accuracy.

4.6. Discussions of the main findings

The findings of this paper could be beneficial to the regulators and the practitioners in various ways. Firstly (*i*), a simple causal interpretation about the less corrupt countries with more cryptocurrency exchanges going into default highlights the complexity of regulatory influence in this space. While it might appear that exchanges in more transparent countries default more frequently, this should not be interpreted as a failure of regulatory oversight. Rather than concluding that regulations are ineffective, the results emphasize that regulations alone may not suffice to ensure the operational stability of the cryptocurrency exchanges. Regulators should understand that while regulations are important, they alone may not guarantee the security and reliability of exchanges. Therefore, cryptocurrency exchanges should focus on implementing robust internal controls and risk management practices regardless of the regulatory environment. Developed countries with high transparency indices, such as the U.S., Switzerland, and Singapore, have the infrastructure, regulatory frameworks, and financial inclusion necessary for widespread cryptocurrency adoption. However, this advanced digital environment also makes them more prone to crypto-related scams, as fraudsters exploit the opportunities created by well-regulated markets and robust internet systems. Logistic regression findings indicate that these nations are more likely to experience cryptocurrency exchange-related scams due to the permissive regulatory environments, while countries with lower transparency indices and less digital infrastructure see fewer incidents due to lower crypto adoption.

Secondly (*ii*), from the logit results presented in Table 4, decentralized exchanges have lower odds of defaulting by 27.5% compared to centralized exchanges. Similarly, the probit results in Table 6 show that the probability of defaulting for a decentralized exchange is lower by 31.2% compared to a centralized exchange. These findings carry important implications for crypto investors, highlighting the significant impact of exchange type on default probabilities. With decentralized exchanges demonstrating significantly reduced default probabilities compared to centralized exchanges, investors may consider allocating their investments towards decentralized platforms to reduce potential default risks. Understanding the nuances of exchange dynamics, particularly in terms of crypto-wallet custody, is crucial. This knowledge can help investors craft a resilient investment strategy within the crypto landscape. In countries with high transparency indices, regulatory bodies enforce stricter compliance standards. While stricter compliance standards may seem beneficial, they also impose significant operational burdens on centralized exchanges. The cost of compliance, coupled with the risk of non-compliance, can strain the financial stability of centralized exchanges, making them more prone to default.

Thirdly (*iii*), the finding underscores the importance of user-friendly fee structures and robust compliance measures. Exchanges must recognize the significant impact of fees on user experience and ensure that fee structures are both competitive and transparent.

High withdrawal fees, in particular, can lead to a decline in trading activity, loss of trust, and decreased competitiveness, ultimately increasing the risk of exchange failure. Thus, maintaining competitive and transparent fee structures is essential for the long-term sustainability of cryptocurrency exchanges.

Fourthly (*iv*), implementing appropriate user restrictions, particularly in jurisdictions with stringent regulatory requirements like the U.S., can help exchanges maintain compliance and mitigate legal risks. While this could imply that regulatory hurdles related to U.S. financial policy are a contributing factor, it is essential to consider various factors holistically. Regulatory hurdles in U.S. financial policy, such as compliance requirements and licensing procedures, may pose challenges for exchanges operating in this jurisdiction. However, the association may also be influenced by other factors, such as heightened legal and compliance risks associated with serving U.S. users, potential regulatory scrutiny, or specific market dynamics. Therefore, while U.S. financial policy and regulatory hurdles may play a role, the relationship between cryptocurrency exchange failure and user restrictions from the U.S. likely involves a combination of regulatory, market, and operational factors.

Regarding the higher likelihood of collapse for exchanges with U.S. customers, while it is true that these exchanges may attract more scrutiny, this does not diminish the validity of our findings. Instead, it emphasizes the role that transparency and regulation play in revealing potential risks, which is crucial for investor protection. The higher visibility of these exchanges does not imply they are inherently riskier but rather that regulated markets are more effective at identifying and addressing issues. Primarily, the idea that DEXs are less prone to collapse is not fully supported by the data. As shown in Table 2, 15% of the total sample consists of DEXs, 12% of default exchanges are DEXs, and 18% of the running exchanges are DEXs. A simple proportional difference analysis in Table 3 confirms that there is no statistically significant difference between the collapse rates of DEXs and centralized exchanges. This finding suggests that DEXs are subject to similar market risks, and their inclusion in the analysis is both relevant and necessary. Furthermore, while one might argue that exchanges in less transparent countries may be safer due to under-reporting or lack of scrutiny, this argument remains speculative. Our analysis includes a diverse range of exchanges across various regulatory environments to mitigate any such bias.

Furthermore, some might argue that centralized exchanges in low-transparency countries are less prone to collapse due to a lack of oversight; however, this perspective does not fully account for the broader risks these exchanges face. While it is true that lower levels of scrutiny might obscure certain vulnerabilities, this does not necessarily mean that these exchanges are more stable. In fact, the absence of transparency may increase systemic risks, potentially leading to collapse without external verification. Our forecasting exercise accounts for these heterogeneities by incorporating transparency and exchange-specific characteristics, ensuring that the predictive model is robust. Additionally, as mentioned previously, decentralized exchanges and centralized exchanges in both high- and low-transparency countries might be subject to similar market factors.

Fifthly (*v*), diversifying coin listings could help exchanges mitigate default risks, as it attracts a broader user base and reduces reliance on a limited range of cryptocurrencies. This diversification not only enhances resilience to market fluctuations and operational risks but also increases revenue potential through trading fees. Exchanges offering a wider selection of assets are more likely to attract traders, establishing a competitive edge over those with fewer options. Traders are more likely to choose exchanges that provide access to a variety of investment opportunities, including both popular and niche cryptocurrencies. As a result, exchanges with few cryptocurrencies may struggle to compete in the market and may experience declining market share over time. This limited revenue stream can make it challenging for the exchange to cover operational costs and remain profitable in the long run.

Finally (*vi*), affiliation programs and ratings play a significant role in decreasing the likelihood of cryptocurrency exchange defaults. By addressing these factors and implementing robust risk management measures, exchanges can enhance operational stability and reduce default risks. Similarly, investors should avoid randomly selecting cryptocurrency exchanges for trading and holding their crypto assets to mitigate the risk of exchange defaults.

5. Conclusion

This study examines the factors leading to cryptocurrency exchange defaults using a sample of 845 exchanges (366 default, 479 non-default) worldwide, based on data available up to February 2023. Logit and probit models identify significant variables, with results showing that centralized exchanges in countries with high transparency indices, offering fewer cryptocurrencies, and imposing high withdrawal fees are more prone to default. Exchanges without U.S. user restrictions are also associated with a higher likelihood of failure. Additionally, the absence of referral schemes and lower ratings each contribute marginally to defaults. These findings align with previous studies, such as those by Fantazzini and Calabrese (2021) and Milunovich and Lee (2022), which identify cybersecurity, exchange age, transaction volume, and the number of cryptocurrencies as key determinants of cryptocurrency exchange survival. However, our study expands on these works by incorporating additional factors, including fee structures, territorial restrictions (such as U.S. client access), ratings, referral programs, bounty programs, certification tests, the centralized or decentralized nature of the exchange, and the transparency index of the exchange's home country. Unlike Mukherjee and Moore (2022), who limit their analysis to a few variables and rely solely on logistic regression, our research includes fourteen distinct factors, providing a more comprehensive analysis of 845 exchanges up to February 2023. The use of machine learning models in our study further confirms the robustness and predictive power of the identified variables, offering deeper insights into the factors contributing to cryptocurrency exchange defaults.

The accuracy of traditional statistical models in predicting cryptocurrency exchange defaults in our study is approximately 81%. Machine learning algorithms, including random forest and SVM, are also tested. The random forest model achieves near-perfect accuracy, while SVM does not significantly improve upon the logit or probit models. K-fold cross-validation confirms the predictive power of all models. GBM performs better in a regular train–test setup, but SVM excels in validation. Neural networks and naive Bayes underperform, while the SEM outperforms all models except random forest by leveraging features from GBM. Furthermore, researching cryptocurrency exchange defaults is crucial to mitigate risks such as scams, security breaches, and fraud, as well as to enhance security and financial management practices, including regular audits and bankruptcy procedures. Regulators, investors, and exchange operators must implement effective policies, maintain adequate reserves, and adopt robust risk management strategies.

The results from this study offer significant insights for both regulators and practitioners in the cryptocurrency exchange sector. Regulators can use these findings to enhance risk assessment frameworks and early warning systems by focusing on factors such as the type of exchange (centralized vs. decentralized), the number of cryptocurrencies listed, and withdrawal fees, which significantly impact default probabilities. For instance, decentralized exchanges exhibit a lower likelihood of defaulting compared to centralized ones, and higher withdrawal fees are associated with an increased default risk. Practitioners, including exchange operators and investors, can leverage this information to refine risk management strategies, such as diversifying cryptocurrency listings and carefully evaluating fee structures. Additionally, understanding the implications of allowing U.S. customers and the transparency in the operation of an exchange can guide strategic decisions and investment choices, ultimately contributing to a more informed and stable financial environment. However, this study has some limitations. First, the use of open-source data may lead to reliability issues. Additionally, endogeneity may arise from reverse causality between predictors and outcomes, which could affect the robustness of the findings. Another limitation is that external financial market conditions, such as monetary policy, are not included in the analysis, potentially omitting an important contextual factor. Furthermore, the logit and probit models employed assume linear relationships, which might introduce bias into the estimates. Future research should incorporate variables such as exchange security practices, financial management, external market conditions, monetary policies, and other regulatory measures to improve the understanding of cryptocurrency exchange failures and provide deeper insights into mitigating risks in cryptocurrency exchanges.

Declaration of competing interest

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

Appendix

See Tables A.1–A.10.

Data availability

Data will be made available on request.

Table A.1
Variable descriptions.

S.No.	Variables	Descriptions	Sources
1	Status	An indicator of whether the exchange is inactive (1) or active (0)	Cryptowisser.com, Coinmarketcap.com
2	DEX	An indicator of whether the exchange is a decentralized exchange (1) or not (0)	Coinmarketcap.com, Cryptowisser.com, Coingecko.com
3	No_cryptos	The number of cryptocurrencies listed on the exchange	Coinmarketcap.com, Cryptowisser.com
4	Wire	An indicator of whether the exchange supports wire transfer (1) or not (0)	Cryptowisser.com
5	Credit	An indicator of whether the exchange supports credit card deposit (1) or not (0)	Cryptowisser.com
6	Taker_rate	The taker fee rate (the fee paid by the person taking an offer)	Coinmarketcap.com, Cryptowisser.com
7	Maker_rate	The maker fee rate (the fee paid by the person making an offer)	Coinmarketcap.com, Cryptowisser.com
8	Withdrawal_fee	The fee rate for withdrawal	Coinmarketcap.com, Cryptowisser.com
9	U.S._allow	An indicator of whether the exchange allows U.S. customers (1) or not (0)	Cryptowisser.com
10	Ratings	This evaluation covers product, infrastructure, user accounts as well as several other security aspects of an exchange. (0,1,2,3)	Coingecko.com
11	Affiliation	An indicator of whether the exchange has an affiliation program (1) or not (0)	Cryptowisser.com
12	Certification	An indicator of whether the exchange has been certified (1) or not (0)	Coingecko.com
13	Pen_test	An indicator of whether the exchange has undergone a penetration test (1) or not (0)	Coingecko.com
14	POR	An indicator of whether the exchange has POR (proof of reserves) (1) or not (0)	Coingecko.com
15	BBounty	An indicator of whether the exchange has a bug bounty program (1) or not (0)	Coingecko.com
16	Transparency	Transparency index of the home country where the exchange is registered	transparency.org
17	*Control_Age*	The age of the exchange, in years, control for survivorship bias	Cryptowisser.com

Note: This table reports the variables, their descriptions, and sources used in this study.

Table A.2
Pearson and biserial correlation matrix.

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1	Status	1.00												
2	DEX	−0.09	1.00											
3	No_cryptos	−0.23	−0.02	1.00										
4	Taker_rate	−0.09	−0.10	−0.15	1.00									
5	Maker_rate	−0.09	−0.09	−0.11	0.86	1.00								
6	Withdrawal_fee	0.17	−0.18	0.02	−0.10	−0.01	1.00							
7	Wire	−0.12	−0.38	−0.03	0.10	0.06	0.04	1.00						
8	Credit	−0.10	−0.18	0.05	0.20	0.18	0.00	0.29	1.00					
9	U.S._allow	0.09	0.20	−0.05	−0.08	−0.07	0.04	−0.12	−0.06	1.00				
10	Affiliation	−0.19	−0.08	0.34	−0.01	−0.01	−0.01	0.14	0.11	−0.08	1.00			
11	Ratings	−0.27	−0.14	0.44	−0.07	−0.07	−0.01	0.14	0.09	0.00	0.26	1.00		
12	Transparency	0.03	−0.29	0.12	0.04	0.06	0.04	0.08	0.09	−0.03	0.12	0.11	1.00	
13	Certification	−0.27	−0.15	0.39	−0.07	−0.07	0.00	0.15	0.08	−0.03	0.20	0.91	0.09	1.00

Note: This table presents the correlation matrix of the variables used in this study. For pairs of continuous variables, the Pearson correlation measure is employed, while the biserial correlation measure is used for associations involving a combination of continuous and binary variables, as well as between two binary variables.

Table A.3
Variance inflation factors (VIFs) of logit and probit models.

S.No.	Variable	Logit model VIF	Probit model VIF
1	DEX	1.4618	1.4449
2	No_cryptos	1.2522	1.2676
3	Taker_rate	2.248	2.3134
4	Maker_rate	2.1732	2.2275
5	Withdrawal_fee	1.1011	1.0973
6	Wire	1.3614	1.3612
7	Credit	1.1655	1.1626
8	U.S._allow	1.0809	1.0801
9	Certification	4.6154	4.7682
10	Affiliation	1.1284	1.1460
11	Ratings	4.7155	4.9027
12	Transparency	1.1480	1.1422
13	Control_Age	1.2207	1.1720

Note:
VIF = 1: No correlation with other independent variables.
$1 < \text{VIF} \leq 5$: Moderate correlation but usually not enough to warrant corrective measures.
$5 < \text{VIF} \leq 10$: Higher correlation; adjustments may be needed.
$\text{VIF} > 10$: Serious multicollinearity; removal or adjustment is needed.
VIF function in the `car` R-package is used to get the variance inflation factors.

Table A.4
Confusion matrix of predicting cryptocurrency exchange defaults using logit model.

Actual group	Predicted group by the logit function	
	Default group	Running group
Default group	272	94
Running group	65	414

Note: This table reports the predicted and actual groups for a binary classification problem of predicting the status of cryptocurrency exchanges (1 = Default, 0 = Running) using a logit model that includes various exchange characteristics as predictor variables. The logit model is presented in Eqs. (1) and (2). The actual groups are shown in the rows, while the predicted groups are shown in the columns. The numbers in each cell represent the count of observations that fall into the corresponding actual and predicted groups. The overall accuracy of the logit model is 81.18%, with a 95% confidence interval of (78.38%, 83.77%).

Table A.5
Predicting cryptocurrency exchange default using probit model.

Actual group	Predicted group by the probit function	
	Default group	Running group
Default group	272	94
Running group	63	416

Note: This table reports the predicted and actual groups for a binary classification problem of predicting the status of cryptocurrency exchanges (1 = Default, 0 = Running) using a probit model that includes various exchange characteristics as predictor variables. The probit model is presented in Eq. (3). The actual groups are shown in the rows, while the predicted groups are shown in the columns. The numbers in each cell represent the count of observations that fall into the corresponding actual and predicted groups. The overall accuracy of the probit model is 81.42%, with a 95% confidence interval of (78.63%, 83.99%).

Table A.6
Random forest and support vector machine accuracy measurement metrics and their interpretations.

S.No.	Metrics	Formulas	Descriptions
1	True Positive (TP)	TP	The number of instances that were correctly predicted as positive
2	False Positive (FP)	FP	The number of instances that were incorrectly predicted as positive
3	True Negative (TN)	TN	The number of instances that were correctly predicted as negative
4	False Negative (FN)	FN	The number of instances that were incorrectly predicted as negative
5	Accuracy	$(TP+TN)/(TP+TN+FP+FN)$	The overall accuracy of the classifier, which is the proportion of correct predictions made by the classifier
6	Sensitivity (Recall)	TP/(TP + FN)	The proportion of actual positive instances that were correctly predicted as positive
7	Specificity	TN/(TN + FP)	The proportion of actual negative instances that were correctly predicted as negative
8	Precision	TP/(TP + FP)	The proportion of positive predictions that were actually positive
9	Negative Predictive Value	TN/(TN + FN)	The proportion of negative predictions that were actually negative
10	No Information Rate	(TN + FN)/(TP + TN + FP + FN)	The proportion of negative instances in the overall datasets
11	Kappa	–	A measure of inter-rater agreement between the classifier and the ground truth, taking into account the agreement expected by chance
12	McNemar's Test P-Value	–	A statistical test used to determine if the difference between the accuracy of two models is statistically significant
13	Prevalence	(TP + FN)/(TP + TN + FP + FN)	The proportion of positive instances in the overall datasets
14	Detection Rate (Sensitivity)	TP/(TP + FN)	The proportion of positive instances in the overall datasets that were correctly predicted as positive
15	Detection Prevalence	(TP + FP)/(TP + TN + FP + FN)	The proportion of positive instances in the overall datasets that were predicted as positive
16	Balanced Accuracy	(Sensitivity + Specificity)/2	The average of sensitivity and specificity, taking into account the balance between false positive and false negative predictions

Table A.7
Random forest confusion matrix (positive class = 1 (default exchanges)).

Actual group	Predicted group by the Random Forest at 60% training data	
	Default group	Running group
Default group	33	3
Running group	3	44
Actual group	Predicted group by the Random Forest at 70% training data	
	Default group	Running group
Default group	34	2
Running group	2	45
Actual group	Predicted group by the Random Forest at 80% training data	
	Default group	Running group
Default group	35	0
Running group	1	47
Actual group	Predicted group by the Random Forest at 90% training data	
	Default group	Running group
Default group	26	5
Running group	10	42

Note: This table reports the predicted and actual groups for a binary classification problem of predicting the status of cryptocurrency exchanges using a Random Forest model that includes various exchange characteristics as predictor variables. The actual groups are shown in the rows, while the predicted groups are shown in the columns. The numbers in each cell represent the count of observations that fall into the corresponding actual and predicted groups at different training data percentages.

Table A.8
Random forest, variable importance at different training proportions.

Variables	at_60%	%ofTotal	at_70%	%ofTotal	at_80%	%ofTotal	at_90%	%ofTotal
DEX	6.2599	3.719	6.5546	3.535	7.8825	3.626	7.2853	3.024
No_cryptos	35.5257	21.107	34.7045	18.717	39.8131	18.316	47.2778	19.624
Taker_rate	18.4054	10.935	22.6266	12.203	26.1944	12.051	30.3778	12.609
Maker_rate	18.7973	11.168	23.5955	12.726	24.6786	11.353	29.4024	12.204
Withdrawal_fee	28.2895	16.808	32.9996	17.798	42.2616	19.442	43.3118	17.978
Wire	5.3266	3.165	6.7473	3.639	7.0490	3.243	7.1562	2.970
Credit	4.1129	2.444	5.0663	2.732	6.4423	2.964	6.6602	2.765
U.S._allow	5.0393	2.994	6.4565	3.482	6.9447	3.195	7.8772	3.270
Affiliation	4.7775	2.839	5.7260	3.088	6.9539	3.199	7.0032	2.907
Ratings	8.0863	4.804	7.8333	4.225	9.7512	4.486	10.452	4.338
Transparency	26.8852	15.974	26.0532	14.051	31.8699	14.662	35.3616	14.678
Certification	6.8032	4.042	7.0502	3.802	7.5266	3.463	8.7514	3.633
Total	**168**	**100**	**185**	**100**	**217**	**100**	**241**	**100**

Note: The variables include U.S. user allowance (U.S._allow), the number of listed cryptocurrencies (No_cryptos), taker fees (Taker_rate), maker fees (Maker_rate), withdrawal fees (Withdrawal_fee), and ratings (Ratings). Binary variables include decentralized exchange status (DEX), certification status (Certification), support for wire transfers (Wire), credit card payments (Credit), affiliation programs (Affiliation), and bug bounty programs (BBounty). The transparency index of the home country is represented by (Transparency).

Table A.9
Support vector machine (SVM) confusion matrix (positive class = 1 (default exchanges)).

Actual group	Predicted group by the SVM at 60% training data	
	Default group	Running group
Default group	112	39
Running group	19	168
Actual group	Predicted group by the SVM at 70% training data	
	Default group	Running group
Default group	91	28
Running group	18	117
Actual group	Predicted group by the SVM at 80% training data	
	Default group	Running group
Default group	60	19
Running group	15	75
Actual group	Predicted group by the SVM at 90% training data	
	Default group	Running group
Default group	30	12
Running group	6	37

Note: This table reports the predicted and actual groups for a binary classification problem of predicting the status of cryptocurrency exchanges using a support vector machine that includes various exchange characteristics as predictor variables. The SVM model is presented in Eqs. (4) and (5). The actual groups are shown in the rows, while the predicted groups are shown in the columns. The numbers in each cell represent the count of observations that fall into the corresponding actual and predicted groups at different training data percentages.

Table A.10
Prediction accuracy of running cryptocurrency exchanges using random forest.

Training data Random Forest	60% RF	70% RF	80% RF	90% RF
Accuracy	0.964	0.952	0.976	0.855
95% confidence interval	(0.898, 0.992)	(0.881, 0.987)	(0.916, 0.997)	(0.761, 0.923)
No information rate	0.566	0.566	0.566	0.566
Kappa	0.926	0.902	0.951	0.708
Mcnemar's test P-value	1.000	1.000	1.000	0.773
Sensitivity	0.979	0.957	0.979	0.851
Specificity	0.944	0.944	0.972	0.861
Pos prediction value	0.958	0.957	0.979	0.889
Neg prediction value	0.971	0.944	0.972	0.816
Prevalence	0.566	0.566	0.566	0.566
Detection rate	0.554	0.542	0.554	0.482
Detection prevalence	0.578	0.566	0.566	0.542
Balanced accuracy	0.962	0.951	0.975	0.856
Positive class	0	0	0	0

Note: This table reports the prediction accuracy of running cryptocurrency exchanges using the random forest model at different training data percentages. Please check Table A.6 to see how the different accuracy measures are calculated.

References

Akyildirim, E., Conlon, T., Corbet, S., Goodell, J.W., 2023. Understanding the FTX exchange collapse: A dynamic connectedness approach. Finance Res. Lett. 53, 103643.
Almeida, J., Gonçalves, T.C., 2023. A systematic literature review of investor behavior in the cryptocurrency markets. J. Behav. Exp. Finance 37, 100785.
Altman, E.I., 1967. The Prediction of Corporate Bankruptcy: A Discriminant Analysis. University of California, Los Angeles.
Altman, E.I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. J. Finance 23 (4), 589–609.
Altman, E.I., Haldeman, R.G., Narayanan, P., 1977. ZETATM analysis a new model to identify bankruptcy risk of corporations. J. Bank. Finance 1 (1), 29–54.
Altman, E.I., Hartzell, J., Peck, M., 1995. A scoring system for emerging market corporate debt. Salomon Brothers 15 (May).
Andersson, M., Chen Trieu, K., Debesay, P., Persson, J., Torrång, J., Utbult, S., 2018. Decentralized cryptocurrency exchange a proof-of-concept based on hashed timelock contracts.
Barbon, A., Ranaldo, A., 2021. On the quality of cryptocurrency markets: Centralized versus decentralized exchanges. arXiv preprint arXiv:2112.07386.
Beaver, W.H., 1966. Financial ratios as predictors of failure. J. Account. Res. 71–111.
Beaver, W.H., Correia, M., McNichols, M.F., et al., 2011. Financial statement analysis and the prediction of financial distress. Found. Trends® Account. 5 (2), 99–173.
Bhimani, A., Hausken, K., Arif, S., 2022. Do national development factors affect cryptocurrency adoption? Technol. Forecast. Soc. Change 181, 121739.
Borri, N., Shakhnov, K., 2022. The cross-section of cryptocurrency returns. Rev. Asset Pricing Stud. 12 (3), 667–705.
Brauneis, A., Mestel, R., Riordan, R., Theissen, E., 2022. Bitcoin unchained: Determinants of cryptocurrency exchange liquidity. J. Empir. Financ. 69, 106–122.
Caliskan, K., 2022. The elephant in the dark: a new framework for cryptocurrency taxation and exchange platform regulation in the US. J. Risk Financ. Manag. 15 (3), 118.
Chatzis, S.P., Siakoulis, V., Petropoulos, A., Stavroulakis, E., Vlachogiannakis, N., 2018. Forecasting stock market crisis events using deep and statistical machine learning techniques. Expert Syst. Appl. 112, 353–371.
Chen, J., Huang, H., Tian, S., Qu, Y., 2009. Feature selection for text classification with Naïve Bayes. Expert Syst. Appl. 36 (3), 5432–5435.
Conlon, T., Corbet, S., Hu, Y., 2023. The collapse of the FTX exchange: The end of cryptocurrency's age of innocence. Br. Account. Rev. 101277.
Dimpfl, T., Peter, F.J., 2021. Nothing but noise? Price discovery across cryptocurrency exchanges. J. Financial Mark. 54, 100584.
Fantazzini, D., Calabrese, R., 2021. Crypto exchanges and credit risk: Modeling and forecasting the probability of closure. J. Risk Financ. Manag. 14 (11), 516.
Feinstein, B.D., Werbach, K., 2021. The impact of cryptocurrency regulation on trading markets. J. Financ. Regul. 7 (1), 48–99.
Fernández, A., García, S., Galar, M., Prati, R.C., Krawczyk, B., Herrera, F., 2018. Learning from Imbalanced Data Sets. Vol. 10, Springer.
Fu, S., Wang, Q., Yu, J., Chen, S., 2022. FTX collapse: a Ponzi story. arXiv preprint arXiv:2212.09436.
Galar, M., Fernandez, A., Barrenechea, E., Bustince, H., Herrera, F., 2011. A review on ensembles for the class imbalance problem: bagging-, boosting-, and hybrid-based approaches. IEEE Trans. Syst. Man Cybern. C 42 (4), 463–484.
Galati, L., 2024. Exchange market share, market makers, and murky behavior: The impact of no-fee trading on cryptocurrency market quality. J. Bank. Financ. 107222.
Galindo, J., Tamayo, P., 2000. Credit risk assessment using statistical and machine learning: basic methodology and risk modeling applications. Comput. Econ. 15, 107–143.
Garcia, J., 2022. Bankruptcy prediction using synthetic sampling. Mach. Learn. Appl. 9, 100343.
Grobys, K., Dufitinema, J., Sapkota, N., Kolari, J.W., 2022a. What's the expected loss when bitcoin is under cyberattack? A fractal process analysis. J. Int. Financ. Mark. Inst. Money 77, 101534.
Grobys, K., Junttila, J., Kolari, J.W., Sapkota, N., 2021. On the stability of stablecoins. J. Empir. Financ. 64, 207–223.
Grobys, K., King, T., Sapkota, N., 2022b. A fractal view on losses attributable to scams in the market for initial coin offerings. J. Risk Financ. Manag. 15 (12), 579.
Grobys, K., Sapkota, N., 2020. Predicting cryptocurrency defaults. Appl. Econ. 52 (46), 5060–5076.
Grone, S., Tong, W., Wimmer, H., Xu, Y., 2021. Arbitrage behavior amongst multiple cryptocurrency exchange markets. In: 2021 International Conference on Computational Science and Computational Intelligence. CSCI, IEEE, pp. 527–532.
Jalan, A., Matkovskyy, R., 2023. Systemic risks in the cryptocurrency market: Evidence from the FTX collapse. Finance Res. Lett. 53, 103670.
Khedr, A.M., Arif, I., El-Bannany, M., Alhashmi, S.M., Sreedharan, M., 2021. Cryptocurrency price prediction using traditional statistical and machine-learning techniques: A survey. Intell. Syst. Account. Finance Manag. 28 (1), 3–34.
Kokorin, I., De Graaf, T., Haentjens, M., 2020. The failed hopes of disintermediation: Crypto-custodian insolvency, legal risks and how to avoid them. Singap. J. Leg. Stud. 526–563.
Lansky, J., 2020. Cryptocurrency survival analysis. J. Altern. Invest. 22 (3), 55–64.
Liu, Y., Tsyvinski, A., Wu, X., 2022. Common risk factors in cryptocurrency. J. Finance 77 (2), 1133–1177.
Lo, A.W., 1986. Logit versus discriminant analysis: A specification test and application to corporate bankruptcies. J. Econometrics 31 (2), 151–178.
Lugovskaya, L., 2010. Predicting default of Russian SMEs on the basis of financial and non-financial variables. J. Financ. Serv. Mark. 14, 301–313.
Ma, T.M., Yamamori, K., Thida, A., 2020. A comparative approach to Naïve Bayes classifier and support vector machine for email spam classification. In: 2020 IEEE 9th Global Conference on Consumer Electronics. GCCE, IEEE, pp. 324–326.
Makarov, I., Schoar, A., 2020. Trading and arbitrage in cryptocurrency markets. J. Financ. Econ. 135 (2), 293–319.
Makridis, C.A., Fröwis, M., Sridhar, K., Böhme, R., 2023. The rise of decentralized cryptocurrency exchanges: Evaluating the role of airdrops and governance tokens. J. Corp. Finance 79, 102358.
McFadden, D.L., 1984. Econometric analysis of qualitative response models. Handb. Econom. 2, 1395–1457.
McNamara, M.E., Zisser, M., Beevers, C.G., Shumake, J., 2022. Not just "big" data: Importance of sample size, measurement error, and uninformative predictors for developing prognostic models for digital interventions. Behav. Res. Ther. 153, 104086.
Milunovich, G., Lee, S.A., 2022. Cryptocurrency exchanges: Predicting which markets will remain active. J. Forecast. 41 (5), 945–955.
Mukherjee, A., Moore, T., 2022. Cryptocurrency exchange closure revisited (again). In: 2022 APWG Symposium on Electronic Crime Research. ECrime, IEEE, pp. 1–8.
Nielsen, D., 2016. Tree Boosting with XGBoost-why does XGBoost Win" Every" Machine Learning Competition? (Master's thesis). NTNU.
Ohlson, J.A., 1980. Financial ratios and the probabilistic prediction of bankruptcy. J. Account. Res. 109–131.
Platt, H.D., Platt, M.B., 1990. Development of a class of stable predictive variables: the case of bankruptcy prediction. J. Bus. Finance Account. 17 (1), 31–51.
Sapkota, N., 2022a. Essays on the New Blockchain-Based Digital Financial Market: Risks and Opportunities. Vol. 491, Vaasan Yliopisto, Acta Wasaensia.
Sapkota, N., 2022b. News-based sentiment and bitcoin volatility. Int. Rev. Financ. Anal. 82, 102183.
Shumway, T., 2001. Forecasting bankruptcy more accurately: A simple hazard model. J. Bus. 74 (1), 101–124.
Ting, S., Ip, W., Tsang, A.H., et al., 2011. Is Naive Bayes a good classifier for document classification. Int. J. Softw. Eng. Its Appl. 5 (3), 37–46.
Tseng, F.-M., Lin, L., 2005. A quadratic interval logit model for forecasting bankruptcy. Omega 33 (1), 85–91.
Vidal-Tomás, D., 2022. Which cryptocurrency data sources should scholars use? Int. Rev. Financ. Anal. 81, 102061.
Wang, J., Yang, J., Iverson, B.C., Kluender, R., 2020. Bankruptcy and the COVID-19 crisis. Available at SSRN 3690398.
Xia, P., Wang, H., Zhang, B., Ji, R., Gao, B., Wu, L., Luo, X., Xu, G., 2020. Characterizing cryptocurrency exchange scams. Comput. Secur. 98, 101993.
Yamak, N., Yamak, R., Samut, S., 2019. Causal relationship between bitcoin price volatility and trading volume: rolling window approach. Financ. Stud. 23 (3 (85)), 6–20.
Zhang, D., Hu, M., Ji, Q., 2020. Financial markets under the global pandemic of COVID-19. Finance Res. Lett. 36, 101528.
Zmijewski, M.E., 1984. Methodological issues related to the estimation of financial distress prediction models. J. Account. Res. 59–82.