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Fintech Unicorns Forecaster: An AI Approach For Financial Distress Prediction

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Abstract

Purpose: *This research undertakes an inquiry into the forecasting of financial distress within the fintech sector, providing valuable insights into the financial health and stability of FinTech unicorns. Through employing an AI technique, a highly accurate financial distress prediction model was created, which also aims to identify and elucidate the pivotal financial variables that influence the prediction of fintech unicorns' financial distress.*

Design/methodology/approach*: This study centers on a dataset featuring prominent fintech unicorns and employs Artificial Neural Networks (ANNs) as a methodological analysis method. Fourteen financial ratios were used in this study to gauge their significance in predicting financial distress among FinTech unicorns.*

Findings: *A classification model was created yielding 95.9% predictive accuracy. In addition, the analysis pinpoints return on capital, current ratio, quick ratio, and the debt-to-equity ratio as significant predictors of financial distress within FinTech unicorns.*

Practical Implications*: This research substantially contributes to the development of a robust and sustainable FinTech ecosystem. It enhances understanding of the financial landscape, benefiting stakeholders, policymakers, and the broader FinTech community by shedding light on crucial aspects of financial health.*

Originality/value: *This pioneering study employs ANNs to explore financial distress prediction within the dynamic FinTech sector, providing crucial insights into factors affecting the financial stability of FinTech unicorns.*

Keywords: *Fintech, Unicorns, AI, ANN, Financial Distress Prediction.*

Introduction

A startup company with a valuation of over $1 billion is referred to as a unicorn. It is frequently employed in the venture capital sector. Aileen Lee[1], a venture capitalist, is credited with popularizing the term. Due to their enormous size, unicorn investors are typically private investors or venture capitalists, making them unavailable to retail investors at the initial phase. The first unicorns were established in the 1990s. Among them, Google stands out with a

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[1] https://techcrunch.com/2013/11/02/welcome-to-the-unicorn-club/

valuation of more than $100 billion. The 2000s saw the birth of many unicorns, such as META. Other well-known unicorns include the financial firms Robinhood and SoFi. Given the extraordinary potential of these companies, this study aims to predict the financial distress of a subset of unicorns, the FinTech unicorns. The paper has important implications for investors and policymakers aiming to preserve financial stability.

New technology that aims to enhance and automate the provision of financial services is referred to as financial technology, or FinTech. FinTech is mostly used to improve how businesses handle their financial operations by employing specialized software and algorithms (Puschmann, 2017). FinTech is a phrase that first appeared in the 21st century and was initially used to describe the technology used in the backend systems of well-established financial organizations, such as banks. However, there is a shift toward services geared toward consumers, which span a variety of fields and professions like education, retail banking, and investment management (Wonglimpiyarat, 2017). FinTech firms, while still new to the financial industry, have used technology to provide notable financial services and solutions. Examples of FinTech innovations include the following: 1) digital payment platforms like PayPal, Square, and Stripe 2) Online lending platforms like Lending Club and Prosper facilitate peer-to-peer lending. 3) Robo-advisors like Betterment and Wealthfront, which provide automated investment advice and portfolio management services using algorithms. 4) Crowdfunding platforms like Kickstarter and Indiegogo enable individuals to raise funds for their projects or business ventures. It is important to note that despite the significant growth that FinTech companies have experienced since disrupting the traditional financial industry, these companies are still vulnerable to financial distress like their conventional counterparts.

Financial distress is a company's inability to meet its financial obligations. It is possible that declining sales, unmanageable debt levels, and inadequate management have contributed to this situation Whitaker, 1999). Financial distress can have severe repercussions, including insolvency, liquidation, and loss of reputation. It is essential for businesses to anticipate financial distress in order to take preventative measures against it. In addition, both industry professionals and academic researchers have shown considerable interest in bankruptcy prediction as an extreme case of financial distress.

The collective collapse of WorldCom, Dotcom, Green Dot, Funding Circle, and Wirecard had a significant impact on usual day-to-day business operations (Clarke and Dean, 2014). Such cases have heightened the importance of accurately predicting the likelihood of bankruptcy. Indeed, there are multiple compelling reasons for highlighting the importance of accurate bankruptcy predictions. In the first place, it is essential for estimating the fair value of loan interest rates. The risk of default influences the calculation of interest rates, which reflect the expense of borrowing money. Secondly, precise bankruptcy forecasting is crucial for evaluating investment risks. Investors can make informed decisions and mitigate potential losses by identifying companies at risk of bankruptcy. In other words, it is a useful instrument for creditors, investors, and managers evaluating a company's "going concern" status. Lastly, the ability to foresee bankruptcy contributes to an improvement in audit quality. Auditors can concentrate their efforts on key indicators of bankruptcy, thereby enhancing the efficacy of their auditing processes. Within the FinTech arena, the failures of Wirecard, Klarna, Funding Circle, and SoFi are a few examples that illustrate the dangers faced by the sector. Such incidents demonstrate that even large, established technology companies are susceptible to financial difficulties.

This study's primary objective is to investigate financial distress predictions (FDP) within the FinTech industry to assess and determine the financial health and stability of these companies. In detail, the study applies Artificial Neural Networks (ANN) to a sample of 32 publicly listed Unicorn FinTech companies to determine the factors predicting financial distress. The data spans from 2019 to 2022. This research ultimately contributes to the development of a resilient and sustainable FinTech ecosystem by enhancing financial landscape comprehension. Moreover, while unicorn businesses are known for their rapid expansion and groundbreaking innovations, they become particularly susceptible to threats, including technology overlaps and ultimately bankruptcy.

This paper provides multiple contributions to the existing literature. First, the study employs an advanced machine learning model, which is known to be superior to traditional statistical methods as they can process a large amount of data and provide promising results in the accuracy of forecasting when compared with traditional statistical methods and time series analyses (Halteh, 2019; Hu et al., 2018; Malagrino et al., 2018). Second, the use of ANNs, in particular, has been shown to possess superior predictive ability even compared with other machine learning techniques (Ahmad et al., 2017; Begum, 2022; Naidu & Govinda, 2018). Third, the paper focus is directed towards the FinTech industry in general and FinTech unicorns in particular, which play a major role as a high economic contributor, as according to KPMG[2], 5,684 global FinTech investments have reached over US$210 billion in 2021. FinTech revenues are also projected to grow sixfold, reaching 1.5 trillion[3] USD by 2030. Finally, merging the machine learning literature with the financial technology sector is another notable contribution. Hence, to the best of our knowledge, this is the first study to focus on the financial distress prediction of FinTech unicorns using a neural network approach.

The subsequent sections of the study are structured in the following manner: The subsequent section (2) provides a review of the relevant literature. Section 3 of this research paper presents an overview of the data source utilized and the methods employed in conducting the investigation. The study's findings are presented in section 4, followed by a comprehensive analysis of the primary outcomes in section 5. The concluding section (6) serves as the culmination of the report and offers insights into the policy implications that may be derived from the study.

2. Literature Review

Numerous academicians have made significant contributions to the field of bankruptcy prediction through their extensive research efforts. In one of the seminal studies conducted by Beaver in the late 1960s, he established a univariate analysis to statistically validate the use of financial ratios in assessing the likelihood of default. Altman (1968) devised the Z-score model, which utilized five financial ratios to forecast the insolvency of U.S. companies. In his investigation of the likelihood of insolvency among a group of businesses, Altman used multiple discriminant analysis (MDA) techniques. Altman's Z-score model has achieved widespread acceptance and is utilized by many, including accountants, banks, auditors, courts, and other creditors. Other researchers have since adopted Altman's methodology, employing MDA techniques under the supposition that variables have normal distributions (see, for example, Deakin (1972); Edmister (1972); Altman et al. (1977); and Grice and Ingram (2001).

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[2] https://kpmg.com/xx/en/home/media/press-releases/2022/02/total-fintech-investment-tops-us-210-billion.html

[3] https://www.bcg.com/press/3may2023-fintech-1-5-trillion-industry-by-2030

Both univariate discriminant analysis and multiple discriminant analysis (MDA) are easy to use and have good short-term predictive accuracy. Nevertheless, they have some limitations. For example, MDA relies on the assumptions of normality and homoscedasticity, which can introduce bias into the results if violated. Additionally, both models have lower predictive accuracy for long-term predictions. However, there has been criticism regarding the assumption of multivariate normality of variables, suggesting that explanatory variables may have different distributions. As a result, the logit model (Ohlson, 1980) and the probit model (Zmijewski, 1984) have gained popularity in bankruptcy prediction as they can handle variables with diverse distributions. Despite their popularity in bankruptcy prediction, logistic models are sensitive to outliers and assume uncorrelated observations. Logistic models may need a larger dataset than MDA for accurate findings.

In recent years, advances in machine learning have facilitated the introduction of new approaches to bankruptcy prediction that frequently outperform traditional statistical methods. There are numerous data-driven and non-parametric variants of these models, such as random forests (RF) (Breiman, 2001), neural network ensembles (Hansen and Salamon, 1990), and gradient-boosting methods (Freund and Schapire, 1997; Friedman et al., 2000; Friedman, 2001). Barboza et al. (2017) conducted a comprehensive study comparing the bankruptcy prediction capabilities of five machine learning models to those of conventional statistical techniques, including discriminant analysis and logistic regression. Their study, based on data from North American companies from 1985 to 2013, demonstrated a significant increase in the accuracy of bankruptcy forecasts when machine learning methods were used as opposed to conventional methods. Shi and Li (2019) conducted a thorough review of the literature and discovered that both logit and neural network models are the most widely used models for bankruptcy prediction. Mai et al. (2018) compared the efficacy of conventional machine learning models and convolutional neural networks using a large database of publicly traded US companies. Their research indicates that simplified models are more likely to accurately predict insolvency. In contrast, Hosaka (2019) found that convolutional neural networks improved the predicted performance of a subset of delisted Japanese corporations.

Gregova et al. (2020) compared traditional (logistic regression) and novel (random forest and neural network) learning algorithm methods to determine the predictive ability and accuracy of Slovak industrial firms. The predictive performance of the new machine learning models is determined to be superior, with the neural network model yielding the best outcomes across all performance characteristics. The study's findings highlight the usefulness of the neural network model for assessing the financial distress of industrial enterprises and its significance for bankruptcy prediction. According to the findings of Lee and Choi (2013), predictions based on industry samples perform better than those based on the entire sample of businesses, and the neural network model provides the maximum predictive accuracy. Chaudhuri and De (2011) assert that artificial neural networks have emerged as the dominant modeling paradigm. Their analysis of the 50 largest insolvent companies with at least $1 billion in market capitalization demonstrates the significance of neural network models used for bankruptcy prediction. However, they assert that the selection of appropriate parameters is crucial to the efficacy of the model. Other research comparing traditional and machine learning models, like Cho et al. (2009), Van Gestel et al. (2010), Kim (2011), Chen (2012), and Nyitrai and Virag (2019), found that models based on discriminant analyses are the worst at making predictions. Linear regression models, on the other hand, do better in almost all cases. According to the findings of all studies cited, learning algorithms offer the highest predictive accuracy.

In their study, Altman et al. (2020) investigate the predictive precision of different estimation techniques employed in evaluating the financial well-being of small and medium-sized firms within an open European market, with a focus on the ten-year period leading up to default. The findings of their study indicate that logistic regression and neural networks exhibit greater performance compared to alternative approaches. Shi and Lo (2019) evaluate the literature on corporate bankruptcy prediction, co-authorship, and the main models and approaches utilized and examined by authors on this subject over the past 50 years. Logistic Regression (Logit) and neural networks are the most commonly used and studied bankruptcy prediction models. Due to computer science and artificial intelligence, this sector has adopted numerous new methodologies, such as machine learning models; however, there is a lack of research that implements machine learning methods in bankruptcy predictions.

Another machine learning technique is Stochastic Gradient Boosting (SGB), which possesses substantial learning capabilities. Freund and Schapire (1996) developed the adaptive boosting method, which serves as the basis for SGB. This technique employs the same training data multiple times and is applicable to numerous group learning algorithms. It contains training case weights that are used throughout the learning process (Witten and Eibe, 2005). Freund and Schapire (1997), Friedman et al. (2000), and Friedman (2001) advanced the concept of boosting as the pioneers of gradient boosting approaches. This method is capable of generating predictions for classification and regression tasks. Before drawing conclusions about crucial parameters and features, boosting begins with the construction of a weak model. On the basis of these findings, a novel and robust multiple-tree model is devised. These trees are generated in an iterative manner to reduce misclassifications. Mueller and Guido (2016) claim that gradient boosting is one of the most efficacious and efficient machine learning techniques available. SGB is more accurate than single models, tagging, and conventional boosting methods and is less susceptible to data contamination from incorrect target labels. In addition, SGB allows for inaccurate data and reduces the need for extensive data preparation, imputation of missing values, and pre-processing steps (Mukkamala et al., 2008).

In their study, Shetty et al. (2022) employed a range of sophisticated machine learning methodologies, including extreme gradient boosting (XGBoost), support vector machines (SVM), and deep neural networks, to forecast bankruptcy based on a dataset comprising 3728 Belgian small and medium enterprises (SMEs) spanning the period from 2002 to 2012. The researchers have demonstrated the ability to forecast bankruptcies with a high level of accuracy, specifically 82–83%, by utilizing a limited collection of easily accessible financial criteria. These ratios include return on assets, current ratio, and solvency ratio. Although the model's forecast accuracy is similar to that of several earlier models discussed in the literature, it is notable for its simplicity in implementation and its effectiveness as a reliable and user-friendly tool for discerning between financially troubled and financially stable companies.

ANNs, decision trees, random forest, and stochastic gradient boosting represent a spectrum of machine learning algorithms frequently employed in both classification and regression tasks. While decision trees offer a straightforward conceptual framework, their predictive accuracy may lag behind more intricate alternatives, particularly when confronted with complex datasets (Halteh, 2019). In contrast, gradient boosting and random forest exhibit admirable accuracy in handling intricate datasets but demand heightened computational resources and extensive data preprocessing. ANNs, due to their capacity to address voluminous data and intricate variable relationships, serve as a preferred choice. Highlighting the diversity of approaches in the field, some studies have expressed a preference for boosting machines and random forests (Barboza et al., 2017; Sakri, 2022). Despite varying preferences observed in empirical studies, ANNs have been found to possess comparable or even superior predictive prowess (Ahmad et al., 2017; Begum, 2022; Naidu & Govinda, 2018). Given the widespread utilization of ANNs in financial prediction literature and cognizant of these findings, this research elects to leverage ANNs for the FDP modeling.

The literature review highlights a gap in the research concerning the utilisation of advanced machine learning techniques for distress prediction pertaining to the FinTech industry in general, and FinTech unicorns in particular. As a result, this study aims to fill this gap by developing an FDP model using a neural network technique to forecast the financial distress of a sample of FinTech unicorns.

3. Data and Methodology

Thirty-two FinTech unicorns were incorporated into this study. These companies were extracted from a report released by the Centre for Finance, Technology, and Entrepreneurship (CFTE, 2023), which ranks global fintech unicorns based on their respective market valuations. 207 companies were on that list; however, as many of these companies are private, they are not required to make their financials public. Data was available for only 32 companies. As per the central limit theorem, a sample of 30 and above is generally considered sufficient to consider that the sample means approximate a normal distribution; thus, an analysis here is feasible.

Four-year financial data (2019–2022) pertaining to the 32 companies was extracted from S&P's Capital IQ, an online portal offering information services that integrate global company data with a range of software tools, enabling financial experts to assess company fundamentals, create financial models, and conduct various financial research activities (Halteh, 2019). S&P has been extensively used across various disciplines in literature, including Feldman and Zoller (2012), Halteh & Sharari (2023), and Kahle and Stulz (2013).

In this study, 14 financial ratios were selected as independent variables. Standard accounting and financial metrics were used to choose these variables because they are common in the existing literature and have been used in previous empirical research (Halteh 2019, Halteh & Sharari 2023, Halteh et al., 2018). You can find a comprehensive list of the variables used in the ANN modeling in Table 1.

Incorporated into the dataset was a binary variable, which was created using the debt-to-equity ratio for each company. After calculating the ratio for each company, the median of the companies' debt-to-equity ratio was calculated for each year. If a company's debt/equity ratio was below the median for that year, it was classified as distressed and assigned a '1'; inversely, companies possessing a debt/equity ratio above the median for the year were considered healthy and given a '0'. This categorization was applied for all the years (2019–2022), and this binary variable serves as the dependent variable in our analysis.

Once the ratios were finalized, the data and variables were imported into the SPSS statistical software, where an ANN model was established using the panel data explained above for the 32 companies across four years, resulting in a total of 128 data fields to be modeled (32 companies x 4 years).

The ANN model was constructed using established settings commonly employed in this type of modeling, as detailed in prior research (Chollet, 2021; Elsken et al., 2019; Halteh, 2019; Halteh & Sharari, 2023):

- Model training involved a random selection of 70% of cases for training and 30% for testing.
- The architecture was automatically selected, allowing the hidden layer to comprise a minimum of 1 unit and a maximum of 50 units.
- The batch training methodology was utilized.
- The optimization algorithm employed was a scaled conjugate gradient.
- Instances with missing values were excluded from the analysis.
- Stopping rules were enacted, with a maximum allowable number of steps without a decrease in error set at 1.
- For the output layer, Softmax served as the activation function, and cross-entropy was the error function.

After meticulous review and confirmation of these settings, the ANN models were primed for execution with the aim of generating results.

4. Empirical results

The case processing steps included in the model are summarized in Table 2, which offers an overview of these steps. During this process, 68.6% of the companies contained within the dataset were selected at random for the purposes of training, while the remaining 31.4% were assigned to be used for testing. In addition, 23 companies were automatically disqualified because the data provided was inadequate.

Table 3 provides a summary of the classification outcomes for the model. In the training phase, the model achieved precise classifications for 84.2% of healthy companies and 88.2% of distressed companies, culminating in an overall accurate prediction rate of 86.1%. In the testing phase, the model correctly classified 83.3% of healthy companies and 93.3% of distressed companies, yielding an overall precise prediction rate of 87.9%.

Figure 1 showcases the Receiver Operating Characteristic (ROC) curve, providing a comprehensive view of possible thresholds, encompassing both true positive and false positive error rates. The area beneath this curve serves as a performance measure for the ROC, with a value nearing 1 signifying enhanced model accuracy (Halteh, 2019). It's clear from the green and blue lines, which signify the model's accuracy, that they occupy a significant portion of the curve. This is quantified in Table 4, where the area under the ROC curve is documented as 0.959 (95.9%).

Figure 2 illustrates the normalized variable importance chart for the ANN model. This chart reveals the top three predictive variables identified by the model, as follows:

1. Return on capital.
2. Current ratio.
3. Quick ratio.
4. Total liability to total assets

The normalized variable importance chart in Figure 2 is very helpful for finding the main input variables that have a big effect on how well the model works. This gives us useful information about the structure of the data and helps us make smart decisions. To gauge the significance of predictors in neural network models, SPSS employs a sensitivity analysis, systematically adjusting input values and monitoring how they influence the output variable. This process helps identify the most critical predictors. Subsequently, the calculation of normalized variable importance involves dividing the absolute value of each input node's weight by the sum of the absolute values of all input node weights (IBM, 2019).

5. Discussion

The results suggest that FinTech unicorns are mostly affected by their return on capital (RoC), current ratio, quick ratio, and the ratio of total debt to total assets. The return on capital ratio, which measures a company's efficiency in generating profits from its invested capital, turns out to be the most important ratio that affects the probability of bankruptcy for FinTech unicorn companies. For such companies, which often require substantial investments in technology infrastructure and market expansion, effectively utilizing capital is critical. A declining RoC may signal inefficiencies or a lack of profitability, potentially leading to financial distress. Fintech unicorns operate in highly competitive markets where sustaining profitability is essential for long-term viability. They frequently attract significant investments to fund their growth and innovation. Ensuring that these investments yield strong returns is crucial for maintaining investor confidence and sustaining operations. RoC helps assess how efficiently they are deploying their capital to generate returns, which is vital in a sector marked by rapid evolution and competition.

The second most important ratio that could predict the bankruptcy of Fintech Unicorn is the liquidity of the company, as measured by both the current and quick ratios. The current ratio is a measure of a company's short-term liquidity and its ability to cover its immediate financial obligations. FinTech companies, like any other, need to maintain a healthy current ratio to ensure they can meet short-term liabilities such as operating expenses and debt payments. If a FinTech unicorn has a low current ratio, it may struggle to cover these obligations, potentially leading to financial distress. Empirical studies in finance and accounting have consistently shown that firms with lower current ratios are more likely to experience financial distress. This is because they may struggle to pay creditors or invest in growth initiatives, especially during economic downturns or unexpected market shocks. In the FinTech industry, where disruptions can be swift and unforgiving, this principle holds relevance. FinTech unicorns are often characterized by rapid growth and high cash burn rates as they seek to scale operations and expand market share. As a result, they may face liquidity challenges if they cannot balance their growth ambitions with short-term financial obligations. The current ratio is a pertinent indicator of their liquidity management.

Furthermore, the quick ratio (current assets excluding inventory divided by current liabilities), which provides a more stringent measure of short-term liquidity by excluding less liquid assets like inventory, is found to be important in predicting FinTech unicorns probability of distress. For FinTech unicorns, which typically do not have significant inventory, the quick ratio offers a clearer picture of their ability to meet immediate obligations. A declining quick ratio may signal liquidity challenges and potential financial distress. Fintech unicorns often prioritize agility and scalability over maintaining large inventories. As a result, their current assets are often more cash- and receivables-focused. The quick ratio aligns with this asset composition and helps evaluate their ability to manage short-term financial commitments without relying on slower-to-monetize assets.

The ratio of total liability to total assets has demonstrated its significance in predicting distress in FinTech unicorn companies. This ratio plays a crucial role in comprehending the debt structure of these companies, as the relationship between debt and equity has extensive implications for these firms. The quick growth of the unicorn requires a significant amount of cash, and while debt can be used to facilitate this growth, overreliance on debt can increase financial risks. The highly competitive nature of FinTech unicorn companies can lead these companies to rely heavily on debt. Hence, it is crucial to underscore the importance of smart credit management within the framework of unicorns, which helps in lessening losses due to credit default. The maintenance of an optimal level of debt is crucial to promoting financial stability within the fintech unicorn sector and reducing their vulnerability to unfavorable economic circumstances.

In summary, the selection of these financial ratios as primary financial distress predictors for FinTech unicorns is justified by their alignment with the specific financial dynamics and challenges faced by these high-growth, technology-driven companies. These ratios provide valuable insights into capital utilization, short-term liquidity management, and the ability to generate profits, all of which are pivotal for the financial health and long-term sustainability of FinTech unicorns. Maintaining an optimal balance between capital utilization (return on capital ratio), liquidity (current and quick ratios), and debt structure is vital for their long-term success and ability to weather economic downturns or industry challenges. Consequently, these factors play a pivotal role in predicting and managing financial distress within this specific subset of the FinTech sector.

6. Conclusions and policy recommendations

In summary, the selection of return on capital (RoC), current ratio, quick ratio, and liability-to-asset ratio as crucial financial distress predictors for fintech unicorns is well-grounded. It aligns with the distinctive attributes of these high-growth, technology-driven companies. These ratios address vital facets of their financial health, including capital efficiency, short-term liquidity, and profitability, all of which are pivotal within the fintech industry's context.

To support the financial health and resilience of FinTech unicorns, policymakers and regulatory authorities should consider several key policy recommendations. Firstly, there is a need to promote capital efficiency among FinTech unicorns. Policymakers can encourage responsible capital allocation by fostering innovative ecosystems, offering incentives for research and development, and facilitating investment in the fintech sector. This will enable these companies to maintain or improve their Return on Capital. Secondly, given the significance of liquidity in the FinTech sector, regulatory bodies should establish guidelines for short-term liquidity management. This includes ensuring that FinTech unicorns maintain adequate cash reserves to meet immediate financial obligations and implementing stress-testing scenarios to assess their resilience during economic downturns. Thirdly, FinTech unicorns should be required to provide regular financial reporting that includes RoC, Current Ratio, and Quick Ratio. Transparent reporting will empower investors and stakeholders to assess the financial health of these firms and make informed decisions. Moreover, regulatory authorities should collaborate with FinTech unicorns to develop risk mitigation strategies, particularly for managing the potential risks associated with rapid growth and external financing. Implementing capital adequacy requirements that align with the specific needs of FinTech businesses is one approach. Lastly, encouraging financial education and literacy within the FinTech sector is essential. Educational programs can help entrepreneurs and decision-makers better comprehend the importance of financial ratios like Return on Capital, Current Ratio, and Quick Ratio. Equipped with this knowledge, FinTech leaders can make informed decisions that promote long-term financial stability.

In conclusion, these financial ratios' selection as critical predictors for FinTech unicorns distress underscores the need for a balanced approach to growth and financial management. By focusing on capital efficiency, liquidity, and profitability, FinTech unicorns can navigate the unique challenges of their industry. Simultaneously, policymakers can provide the regulatory framework and guidance necessary to promote sustainable growth and financial stability within the FinTech sector.

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