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Utilizing AI in the Middle and Back Offices of Banks for Risk Mitigation

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ABSTRACT

In March of 2022, Silicon Valley Bank collapsed in a large-scale bank run, causing the bank to be placed under the control of the FDIC. Consequently, similar bank failures occurred, such as the collapse of First Republic Bank. These failures were in part caused by lack of oversight on long-term and short-term investments, which continue to threaten banks today. However, with novel AI technology in the middle and back offices of banking institutions, many of these risks might be mitigated. Using a wide variety of models, banks can use artificial intelligence to mitigate credit risk, operational risk, financial crime, security breaches, and macroeconomic risk. While these solutions can be time and cost-effective, they do have significant roadblocks associated with them, such as the lack of scalability, possible conflict with ethics and regulatory mandates, and a decrease in job opportunities due to heavy automation. However, each of these barriers to success has a solution which allows banks to more easily implement AI into their infrastructure.

An Overview of Recent Banking Crises

Silicon Valley Bank

Before March 2022, Silicon Valley Bank ("SVB") was a successful bank, working with many large companies from Silicon Valley, mainly venture capital backed companies (Federal Reserve System, 2023). One example is Roku, which deposited a staggering $487 million of its $1.9 billion cash with SVB (Maruf, 2023). SVB had $209-212 billion in total assets (Federal Reserve System, 2023). During their operating years, SVB poured 21 billion dollars into government bonds and, specifically, US Treasury bonds (Reuters, 2023; Federal Reserve System, 2023). While government bonds are generally less risky, they are affected by something known as interest rate risk, where the value of bonds can change given change in interest rates (Metrick, 2024). SVB bought the securities while interest rates were still low, so the bank experienced growth, with its growth tripling between 2019 and 2021 (Metrick, 2024; Federal Reserve Bank, 2023). However, as the government raised them to combat inflation, SVB's bonds plummeted in value (Knowledge At Wharton, 2023). So, their bond portfolio was only growing at an average rate of 1.79%, rather than the 10-year Treasury yield at the time, which was 3.9% (Reuters, 2023; UW School of Law, 2023). In addition, rising interest rates also increased borrowing costs, or the amount of money needed to borrow new capital. Rising borrowing costs forced many tech startups, the main clients of SVB, to start withdrawing their assets to pay off their debts. Finally, SVB had a large amount of uninsured deposits, which were deposits that could not be insured by the FDIC, making up around 94% of SVB's entire portfolio (Metrick, 2024; Federal Reserve System, 2023).

The final domino that triggered SVB's collapse was SVB announcing it had lost $1.8 billion after needing to sell $24 billion dollars worth of securities at a loss, all the while detailing a plan to do an equity offering of approximately $2 billion (Metrick, 2024; Knowledge At Wharton, 2023; Federal Reserve System, 2023). Public customers went into a selling frenzy after the announcement of the plan, and on March 9, 2023, over $42 billion dollars worth of deposits was withdrawn from the bank (Metrick, 2024; Raffio, 2023; Knowledge at Wharton, 2023). When SVB's stock plunged to 60% of its original value, regulators intervened and placed the bank under control of the Federal Deposit Insurance Corporation ("FDIC"), where it would be liquidated (Ziady, 2023; Metrick, 2024). In total, investors lost approximately $72 billion (Knowledge at Wharton, 2023).

Numerous detrimental factors caused the SVB failure, but most have one thing in common: poor decision-making. Lack of foresight (not thinking about the scenario when interest rates would rise, creating a static portfolio) and poor investments (the securities that SVB lost money in) ultimately caused the bank to be liquidated. Ultimately, the main source of blame for the SVB failure continues to be a lack of strong investment decisions (Raffio, 2023).

First Republic Bank

First Republic Bank's ("FRB") primary business model was providing large loans and mortgages with lower interest rates to its customers (Delevingne, 2023). These low-interest rates often attracted wealthier customers, like Instacart founder Apoorva Mehta and real-estate developer Stephen Ross (Delevingne, 2023). FRB's shareholder returns were phenomenal, at nearly 19.5% compounded annually (Delevingne, 2023). However, similarly to SVB, around $119.5 billion (nearly 70%) of its portfolio was uninsured deposits (Gruenberg, 2024). Each of these uninsured deposits overstepped the FDIC's guaranteed limit of $250,000 per depositor (Cheung & Wile, 2023). Additionally, the bank possessed a significant number of long-term loans, which, like in SVB's case, lost value as the Federal Reserve increased interest rates (Columbia Business School, 2023).

Furthermore, FRB was challenged by bad publicity following the recent closure of SVB, and it was already at risk since previous bank failures were also due to large percentages of uninsured deposits (Gruenberg, 2024). This led a growing number of consumers and investors to become concerned over their investments in FRB. On April 24th, 2023, FRB stated that it had lost around 41% of its deposits during the first quarter of 2023, which caused the stock price to decrease by 95% of its original size (Saul, 2023). The FDIC seized all of FRB's holdings, selling them to the highest bidder, JPMorgan Chase (Columbia Business School, 2023).

The failures of both SVB and FRB share similarities. For example, both demonstrated a lack of forward-thinking regarding interest rate hikes and investments. FRB held too many uninsured deposits, which caused heavy losses for both consumers and the bank (Hyatt, 2023). Additionally, it had loans that started to depreciate as interest rates rose (like the government bonds that SVB held). Both failures and subsequent FDIC seizures may have been prevented with better predictive technology and investment analysis.

The Effects and Frequency of Bank Failures

Bank closures, like with SVB and FRB, are highly detrimental. The scale of adverse effects is illustrated by the aftershock of many of these bank failures. For example, Credit Suisse suffered after one of its most prominent investors said that it could no longer provide money to the bank. Credit Suisse's stock prices tanked globally, and the central bank of Switzerland had to lend $54 billion to help calm investor turmoil—bank closures, even in just one country, have ripple effects worldwide (Shine, 2023). These banks and their failures are also tied to each other, as seen with FRB. This is part of a general effect called systemic risk, where bank runs on one bank can cascade and lead to lower confidence in others, also called a contagion (UW School of Law, 2023).

Additionally, bank closures could teeter the world onto the edge of a global recession. A global recession is when there is an extended and widespread shutdown of the economy all over the globe, and heavy unemployment is present (Halton, 2021). The most distressing piece of data is that bank closures are only rising in frequency. After the failures of SVB, FRB, and other large banks like Signature Bank, studies found that a staggering 186 more banks could follow suit (Ramaswamy, 2023). If these banks close, there would be impacts for the global economy.

With the looming threats posed by bank failures, banks need solutions to help stave off unnecessary risks and improve the experience between themselves and their consumers. However, banks have several intricate functions that must work in tandem to deliver financial solutions to customers and increase value for their investors. This complexity must be adequately addressed to ensure the proper financial health of banks (UW School of Law, 2023). So, a risk management system that can handle complexity is necessary. Recently, with the rapid advancement in its technology, artificial intelligence is poised to help banks run their risk management systems and handle complex business processes with efficiency.

Artificial Intelligence & Banking: Terminology, Structure, and Vulnerabilities

Information on AI

Artificial intelligence (AI) is a machine or agent which can take in information from its environment (stimuli) and use that to make a decision based on its objective (Haruna, 2020). This external stimuli is perceived as data which the AI then uses to make a decision. The intelligence of the system, as opposed to any other computer algorithm, is that it learns from past iterations to make more successful decisions in the future. Artificial intelligence's ability to take stimuli and become more successful through each iteration allows it to handle higher levels of complexity than most other computer programs.

One important distinction to make is between AI and machine learning (ML). Machine learning also consists of a system which learns from data, but it is distinct from a complete AI because humans dictate the data which goes into the system and how the output is used (Aziz & Dowling, 2018). Machine learning contrasts with a complete AI, which takes input and uses its output on its own without human supervision. At this moment in time, one of the most feasible options would be to use machine learning, but as AI continues to develop, human involvement with data feeding and processing will probably become increasingly little. The type of ML that should be applied for banking operations is called deep learning. Deep learning uses neural networks to make fast calculations on data which expedites the learning process (Mathew et al., 2021).

There are three main ways that deep learning algorithms learn. In supervised learning, a set of inputs are matched to outputs, and those values are used to determine the function that transforms input into output for future calculations. In unsupervised learning, there is only input fed into the algorithm, and the algorithm has to find patterns and structures within the data. Finally, there is reinforcement learning, which works by providing negative consequences to a machine which is not close to its target, but generates an award when it grows nearer to its target. Within the organization of banks, all three algorithms can be utilized productively and are each particularly effective in specific areas of operation (Mathew et al., 2021).

Information on Banks

Banks, like many financial institutions, have a structure in which several parts are delegated with different duties. In banks, these are known as offices, and there are three offices with different distinct functions.

Firstly, there is the front office, which is the portion of a firm which deals directly with customers. This portion of a bank usually handles reception. However, in many scenarios, other services can also be directly provided to a customer which aren't necessarily just related to reception (Dollarhide, 2024). Secondly, there is the middle office. The middle office of any firm is the section which analyzes and manages risks. More specifically, the middle office of a bank will certify the success and security of any transaction by making sure it is properly executed. This is also the section of the bank with the highest access to information technology (Kopp, 2024). Finally, there is the back office, which does not directly interact with the customers of a firm; it supports the front and middle offices in carrying out their roles. The back office provides support functions for the rest of the firm, such as accounting and other important jobs which are not handled by the other two offices (The Investopedia Team, 2024b). The front and back office's jobs are inextricably linked through the middle office, and any significant effect on one could have an effect on the other.

AI's Utility for Risk Management

Artificial intelligence may be useful in generating an understanding as to what causes bank failures. Bank failures, and any bank shortcomings, generally occur due to an array of risks pertaining to the bank. For example, one prominent risk is economic factors. Global and national economic fluctuation can make it difficult to predict change within a bank's revenue and can harm the bank in term (Dell'ariccia, G. & Marquez, R., 2010). Another important risk to consider is credit risk, or the risk that a borrower is not able to pay back their loan, leading to adverse effects for banks (The Investopedia Team, 2024a). It is also important to note that these risks go hand in hand, since changes in a nation's economy can cause changes in loans, making them more difficult to pay and leading to credit risk. Another factor in bank failure is liquidity. The over creation of liquidity in a bank system can cause and spread bank failures across a wide area (Fungacova et al., 2021).

Artificial intelligence helps mitigate bank failures in a variety of ways. This technology can handle the complexity of various factors, and it is positioned well to help banks achieve stability (McPhail & McPhail, 2019). Its ability to take in external stimuli in order to make adequate decisions is paramount in a rapidly fluctuating economic environment. Additionally, the many types of AI training can be used in banks in several different ways, as banks require a need for both supervised and unsupervised architecture. Finally, since most of the risk management and accounting business is handled by the middle and back offices of a bank, AI could be stationed within those functions. It can adeptly manage the various different economic statuses to remember and track while also being efficient. When trained correctly, AI is a useful tool to make more accurate guesses on information that is provided. AI is also useful in the back office of banks because of the repetitive nature of back office tasks, which can be sped up (Gokani, 2017).

Implementing AI For Risk Control

General Uses of AI For Risk Control

While AI has many distinct uses in banks, the main focus of this paper is AI's use in the middle and back offices of a bank. The middle office most commonly relates to risk recognition protocols, such as fraud detection, and the back office pertains to accounting and financial information. Since these two areas of a bank have the most risk-related procedures, they will be the focus of this paper.

Since the 2008 financial crisis, an emphasis has been placed on risk mitigating technologies, often referred to as RegTech, which can shrink costs and lead to increased compliance with regulatory standards (Boukherouaa et al., 2021). When it comes to managing risk, the most influential areas are credit risk, operational risk (internal risk management), real-time transaction analysis, biometrics for authorization, and macroeconomic predictions.

Credit risk is essentially the financial risk of a borrower not paying back a loan (The Investopedia Team, 2024a). When borrowers fail to pay back loans in time, the banks are subject to financial losses. An AI which assists in mitigating credit risk helps to determine which people are more "creditworthy" when lending, protecting against those financial losses (Davis et al., 2022). Since credit risk often involves looking at long periods of time, ML is an invaluable tool for looking over all the information and using it to determine the creditworthiness of customers. The specific way that ML does this in banks is through enhanced effectiveness of current modeling structures, such as models for probability of default, loss given default, and exposure at default (Folpmers, 2023). This type of tool will utilize non-supervised learning since it has to find patterns in large sets of data that do not already have distinction.

Operational risk refers to a type of risk that centers on the activities of a bank itself rather than its surroundings (Segal, 2024). This includes the structure of the bank, how it spends its capital, and its strategies. Another way that operational risk can be described is as human failures, since it results from inaccuracies caused by human error (Segal, 2024). In banks, operational risk is prevalent and it is crucial that it is managed effectively. This means monitoring the exposure that the bank has with risks, understanding the cash flow of the bank to understand where capital is being utilized, and making sure that the bank's operations are in line with regulations and laws (Basel Committee on Banking Supervision, 2011). Any bank should be constantly reviewed and inspected to ensure it's health (Metrick, 2024). One way that AI has been directly applied to operational risk management is through liquidity management, which ensures that banks are aware of the true status of their capital (Geczy, 2024). In addition to this, ML should be utilized to perform constant checks of banking processes to make sure that they are compliant with the law. Understanding patterns regarding cash flow can be done with unsupervised learning; however, supervised learning can be utilized to train the ML to understand rules and regulations with positive examples.

In order to prevent financial crimes, banks and other financial institutions need a method to monitor incoming transactions to determine wrongdoing. Real-time transaction analysis would help. By examining transactions going through a bank and analyzing them in real time, the system can provide immediate feedback (Financial Crime Academy, 2024). One instance of this being used is anti-money laundering (AML), which reports suspicious account behavior (Gokani, 2017). With the use of ML, patterns can be more quickly and accurately recognized in a series of transactions, which ensure that banks catch illegal activity. Researchers from the Rochester Institute of Technology demonstrated that when testing AI models to recognize fraudulent activity, it could train models to be up to 99.79% accurate on test data (Al Marri & Al Ali, 2020).

When it comes to ensuring security of banks, biometrics is a helpful tool. Biometrics uses biological features such as fingerprint, voice patterns, and facial identification in order to confirm the identity of a customer (Gregory, 2019). AI has already begun to use deep learning networks in order to be more accurate in non-standard situations, such as different angles of a face (Berghoff, 2021).

While managing internal risks is extremely important when managing and mitigating a bank's overall risk, it is also important to constantly evaluate the economic environment of the bank. This evaluation is known as macroeconomic forecasting, and it usually looks at a smaller amount of data over long periods of time to assess the macroeconomic environment. One branch of this is called sentiment analysis, which measures macroeconomic health through the sentiment of populations, which is generally more accurate at predicting macroeconomic health than other methods (McPhail & McPhail, 2019; Parameshwaran, 2023).

Specific Use Cases and Outcomes of AI in Risk Control

Many banks have already implemented AI utilities into their daily operations. One large bank which has begun to utilize AI for risk control is Barclays. Barclays has initiated a form of Real Time Transaction Analysis in order to find out cases where fraudulent transactions are taking place (Fernandez, 2023). Alongside these projects, they are also taking part in predictive AI to mitigate credit risk, partnered with a company named Simudyne, and automated credit card deactivation with IBM (Mejia, 2020). Barclays will continue to use AI, and even branch out to forms of AI which could benefit them more, such as generative AI.

Another large banking institution which is beginning to utilize AI is Banco Santander. In particular, Banco Santander has used AI in order to manage the data of its customers (Santander, 2022). Their most relevant system to directly manage banking risks is called Kairos, which is a utility which helps predict how clients of the bank can be affected by different economic externalities (Fernandez, 2023). Their online bank has also offered a stock price prediction service using AI, which can be utilized for over 1000 stocks (Montijano, 2024).

J.P. Morgan Chase has also utilized AI for legal document analysis, with a system called Contract Intelligence. This system helped analyze 12,000 credit agreements in a matter of seconds, which is a job that would have otherwise taken hundreds of thousands of human hours (Gokani, 2017).

Alongside AI being developed within many financial institutions, there are also start up companies who partner with banks which utilize AI to manage bank risks. One such company is Feedzai. Feedzai is a risk mitigation software in transaction fraud, AML, compliance checking, customer profiling, and more (Gokani, 2024). Another such app is known as Chorus. Chorus specializes in financial crime analysis, and can help users such as banks understand if any illegal activity is occurring within their system (Chorus Intel, 2024).

Roadblocks of AI Implementation in Banks

While AI has been useful in banks, there are also prevalent roadblocks which are currently preventing them from being adequately utilized. Many of these roadblocks occur because of the sheer amount of data being collected and a necessity for risk mitigation to be done without error. However, many of these roadblocks can also be surpassed, with a combination of transparency, error handling, and continuous improvement. The main roadblocks preventing AI from being used in banks are data shortage and access concerns, ethical and regulatory concerns, and workforce replacement. Each is described in this section.

Data Shortage and Access

The benefit of AI stems from having large data sets to learn from, but it is incredibly difficult for banks to utilize all the necessary data. The reason for this is not the machine learning algorithm, but rather that banks need to accurately organize their information (which is often stored in multiple different sectors with different regulations), which hasn't been done at the same speed as machine learning advancements (Aziz & Dowling, 2020). In the same vein, not all data might be accurately represented for an AI. The data that AI uses can come from various sources of previously untapped data. While this may seem like a positive aspect at first, it also brings up issues regarding the quality of the data and ethical questions (Boukherouaa et al., 2021). One specific example of a bias which is created is with providing loans based on credit, where AI can unwittingly be trained to have biases against minorities (Andrews, 2021). This is not because the AI is programmed to have that bias, but it acquires that bias from the data because the credit data from minorities groups is often more limited. The quality of the data is especially important, since data which is not clean can produce "hallucinations," or outputs which make little to no sense (Baxter & Schlesinger, 2023). Finally, much of the data that banks possess is confidential, so using it in AI might accidentally breach security (Fernandez, 2023).

The roadblock of data access can be fixed with a fundamental restructuring of data access in banks. Instead of traditional data storage, which is where data is stored in various silos, a system where all data can be labeled and accessed by a variety of bank operations will allow for easy and immediate use of data (Biswas et al., 2020). To ensure that data is clean for use, it is recommended that banks use zero-party data (in which customers actively share the information), first-party data (data which a bank itself collects), and continually check validity to ensure there are no errors or outdated pieces of data which could hinder the AI (Baxter & Schlesinger, 2023). This will also mitigate security concerns, since only getting data which the customer has consented to nearly eliminates the possibility of security breaches.

Ethical & Regulatory Roadblocks

While AI is an extremely useful technology for tasks which require such large amounts of data, problems arise from its lack of transparency (McPhail & McPhail, 2019). As discussed in Section II, AI takes data from an input layer and puts it through various hidden layers before giving the output data in an output layer. However, since these layers are "hidden," the operations which they are performing cannot be seen by the bank, making it a less effective method of risk management as well as a source of issue when it comes to regulation (Aziz & Dowling, 2018). This can be especially detrimental in a financial context if AI produces a hallucination which leads to an expensive mistake, which also can't be easily fixed without knowing the processes which the AI used.

Additionally, there are ethical concerns about bias, where it is crucial that no one is unfairly discriminated against by the AI in use. Although these issues might be specifically blocked by whoever creates the AI, discrimination can still happen through an unconscious "selection bias" (Aziz & Dowling, 2018; Fernandez, 2023). This occurs because of the bias that is already present in banks and their data, which the AI system is then trained on (Ajanaku, 2022). This carries on the bias technologically, even if there are specific measures in place which try to prevent such bias.

However, there are methods to mitigate both of these ethical and regulatory roadblocks to implementing AI in banking settings. Handling the transparency of the AI by going through every single step of how the AI works is not the best solution. Rather, the basic way that the AI works should be provided by the developers to ensure that the processes being performed are understandable to the user (Zicari, 2018).

When it comes to selection bias and other biases, a method to determine the prevalence of an AI's bias is "blind taste testing." In blind taste testing, a model is given all the data necessary and ran, but in another scenario, data that can cause bias is denied and the model is run again. If the results are similar, it means that the AI has little to no bias to that specific variable. However, if there are differences, the AI model needs to be changed to reduce the bias significantly before its use (Uzzi, 2020). Combined with monitoring and the inclusion of systems where possible to detect bias, bias in the AI can be mitigated.

Workforce

The final major roadblock pertaining to AI stems from the workforce. This affect isn't central to the banking industry, as it is estimated that 14% of employees are expected to lose their jobs by 2030 because of automation, and replace up to 30 million jobs across the globe (Talmage-Rostron, 2024). Some estimates even show that 50% of jobs are at risk of being displaced by AI (Parker, 2018). Predictions estimate that up to 54% of all jobs across banking could be automated (Gani, 2024). In banks specifically, tasks that involve mathematical or verbal skills will be subject to high amounts of AI, which removes the potential for many of the jobs that could be produced in those sectors (Hernandez, 2023). Additionally, changing to an AI based framework for work will mean that many workers will need additional AI training to succeed in their jobs (Rainie & Anderson, 2017).

Workforce related roadblocks can be averted with two methods. Instead of replacing human jobs with AI jobs, human jobs could be integrated with AI in a way that both the human worker and the banking system as a whole (Hernandez, 2023). The synergy of AI and humans is crucial because both systems exhibit unique skills, where AI is more logical and analytical, and humans are more emotionally sensitive, so the work that they do together has a higher potential of producing a good outcome (De Cremer & Kasparov, 2021). With only sentiment or only logic, a job wouldn't be done as productively and effectively compared to if both were simultaneously utilized.

Conclusion

The main cause of the failures of Silicon Valley Bank and First Republic Bank was shown to mainly be related to poor decision-making and improper risk management within the banks. The failure of a bank does not just have an impact on its employees and customers: the failure of a bank can have a cascading, negative effect on global economies. AI can be utilized to mitigate risk in the middle and back offices of banks dealing with credit risk, operational risk, market risk, real time transaction analysis, and biometrics for bank security. Examples of real industry use were provided, in each case pertaining to the risk management aspect needed in banks. Finally, there are roadblocks preventing AI from being implemented, mainly surrounding data shortage/access concerns, ethical and regulatory reasons, and workforce demands. However, each of these cases also had a system to mitigate the issue, which should allow banks to utilize AI on a far wider scale.

In an advancing digital age, the transition of banks to an AI centered model for responding to risk will be crucial. In an ever-growing dataspace, AI will be the way that risk is ultimately minimized in the most efficient manner, and when implemented properly, will see to the success of the bank. Perhaps if AI was more heavily utilized in Silicon Valley Bank, machines would have caught on to the increasing risk of buying securities given macroeconomic forecasts and other factors and caused executives at the company to reconsider and move forward with a different strategy. In First Republic Bank, machines could have been able to detect the regulatory error and inherent issues with issuing the number of uninsured deposits that it did. With AI, banks will be more secure, leading to the prosperity of the bank, and ultimately, the security of the assets.

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