Impacts of Artificial Intelligence Technology to Customer Credit Evaluation in Banking and Finance Industry

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May 24, 2022

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Abstract

This paper aims to review previous literature related to the application of artificial intelligent (AI) technologies in finance. The method of systematic literature associating the topics of AI Technology and customer credit evaluation is utilized. Based on the review, several key findings were identified. Firstly, the importance of credit evaluation can be recognized from the Key of AI technologies in the financial sector. Secondly, the contributions of AI are mainly in the optimization of the credit evaluation system, which can significantly reduce the risks and costs that need to be considered in the financial sector. Thirdly, potential limitations of AI include that it is not subject to human intervention; therefore, AI is unable to analyse customer information without considering the customer's emotional and behavioural issues, which leads to mistrust and resistance to AI from customers. Moreover, banks or financial institutions cannot hold AI accountable when its analysis is flawed or faulty. In the event of specific risks, the first responsible party cannot be found. However, there are limitations of this research, for example it does not incorporate empirical evidence. Therefore, future research is needed to obtain data related to AI in finance through observation and experimentation. Research hypotheses could then be formulated and tested to investigate this research question further.

Keyword: Artificial Intelligence; Credit Evaluation; Banking and Finance Industry

1. Introduction

In recent years, artificial intelligence has covered almost all major areas of real life, including business activities, security systems, and financial markets. Artificial intelligence (AI) has developed rapidly over the last decade as a general-purpose technology (Taddy, 2019). Fundamentally, it is the simulation of human intelligence processes through computer systems (Kumar and Thakur, 2012). Artificial intelligence develops theories, methods, technologies, and applied techniques for simulating, extending, and scaling human intelligence through research that can reason and perform specified operations (Deng, 2018).

The future workplace (2018) estimated that approximately \$22 billion was spent on AI in the business sector in 2017, 26 times more than in 2015. In their study, Furman and Seamans (2019) stated that the error rate of AI recognition of images fell from 29% to 3% between 2010-2017, exceeding the level of human performance. Although AI technologies are becoming more powerful, they are still limited as they cannot achieve a 100% accuracy and are challenging to pre-test and deploy. Specifically, AI's algorithms, based on neuronal networks, lack the cognitive abilities that multibiological brains take for granted.

The purpose of this paper is to survey and review previous literature on the use of AI in financial markets (e.g., Bahrammirzaee, 2010; Brenner and Meyll, 2020;

Bhatia, Chandani and Chhateja, 2020; Khandani, Kim and Lo, 2010; Kö nigstorfer and Thalmann,2020). Many papers on the application of AI in finance have examined the use of AI technology in financial markets. While AI can make sound evaluations of 4 customer information, the attendant limitation of AI has had a non-negligible impact. In this context, the following section discusses the application of AI in the financial markets.

2. Review of AI and Credit Evaluation Research

AI is gaining attention in financial decision making within the financial market. AI can help the financial industry better target customers, optimise business operations, improve profits, as well as reduce risks and costs through computing (Alfaro et al., 2019).

This section is divided into three parts. The first reviews the relevant importance and necessity of efficient credit evaluation in the banking and finance industry. Secondly, AI-enabled credit evaluation in the banking and finance industry is discussed. Finally, potential limitations of AI applications in credit evaluation are identified.

2.1 The importance and necessity of efficient credit evaluation in banking and finance industry

The importance of customer credit assessment in banking and finance is analysed from several perspectives, including the purpose of risk analysis and relevant data to provide data support for credit assessment and risk analysis. Customer credit evaluation and risk analysis are essential topics in banking and finance. Customer credit scoring assesses the risk associated with a loan to an organisation or individual. When banks grant loans, they need to assess whether borrowers can repay them (Mhlanga, 2021). The purpose of risk analysis is to understand the investor's investment objectives, financial situation, attitudes, and risk tolerance. It is necessary to determine the investor's risk tolerance range in the financial sector to determine risk appetite and conduct a comprehensive risk analysis (Nevins, 2004). According to Norrestad (2021), the UK's total monthly outstanding consumer credit from April 2018 to March 2020 was over £225.2 billion (Figure 1). Moreover, the average household mortgage balance continues to rise, with the average amount outstanding increasing from £103,657 to £142,183 per household from 2006 to 2019, as shown in Figure 2. As a result, banks conduct an essential assessment of customer credit and risk analysis to judge whether a customer has sufficient repayment capacity and risk tolerance.

Credit evaluation is one of the most critical processes in banks' credit management decisions. This process is the decision to collect, analyse, and classify different credit elements and variables to assess a customer's credit. When a bank receives a customer's loan request, it performs a standard credit assessment and makes an acceptance/rejection decision to lend based on this assessment (Abdou and Pointon, 2011). Anderson (2007) viewed credit assessment as a statistical model to analyse whether a borrower has the potential to default on loan and become insolvent. Abdou and Pointon (2011) argued that the quality of loans is an essential factor for banks to compete, survive, and make a profit in the industry. Credit scoring, as part of the credit assessment process, reduces the current and expected risk of poor credit of customers. Thus, a credit assessment is an analysis of a customer's personal credit information, which objectively examines the intrinsic and extrinsic factors affecting individuals and households. The bank's interests are protected by a comprehensive assessment of the customer's ability to meet various financial commitments.

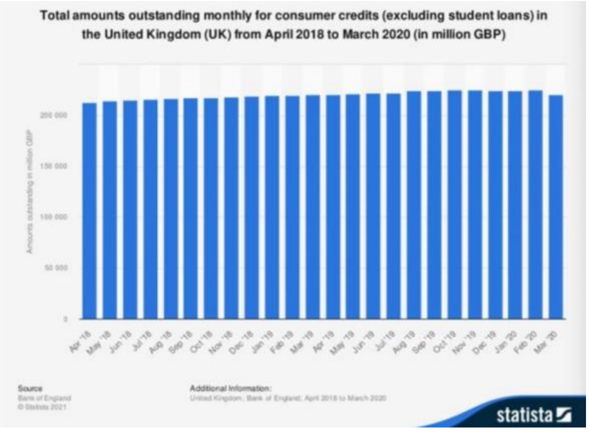

Figure 1: Total amount outstanding monthly for consumer credits in the United Kingdom (UK) (Norrestad, 2021)

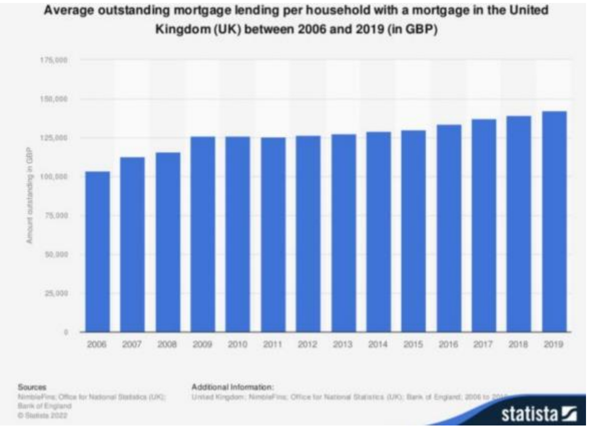

Figure 2: Average outstanding mortgage lending per household with a mortgage in the United Kingdom (UK) from 2006 to 2019 (Statista, 2022)

2.2 AI enabled credit evaluation in banking and finance industry

The contribution of AI to credit assessment will be discussed from several perspectives, including the changes AI has made to financial markets and the assistance it provides to banks and financial institutions in hedging risk and reducing costs.

Firstly, with the aid of AI functions, Machine Learning and Deep learning, credit scoring models, and mechanisms can be involved in a continuous improvement process. Compared with the traditional static model, AI technology can incorporate a dynamic process combining various sources of data and optimising the model using algorithms. Nevins (2004) agreed that risk analysis in the financial sector identifies and analyses customers' risk appetite and repayment capacity by determining their current financial situation, attitudes, and risk tolerance. Similarly, Chhabra (2005) suggested that AI can effectively help the financial industry understand customer segments, segment customer needs, and develop practical solutions to meet these unknown segments. For example, risk appetite, number of family members, number of dependents, current income, risk profile, short- and long-term goals and obligations, liabilities, age, available capital resources, liquidity, and current asset allocation. Harasim (2016) pointed out that the whole spectrum of commercial banking can benefit from AI, which can correctly assess a customer's credit rating and ensure that banks can reap the benefits of lending. Biallas and O'Neill (2020) showed that AI analyses and validates the ability of customers to repay loans by assisting banks in assessing their assets.

Secondly, taking advantage of AI algorithms, such as clustering and decision tree, credit evaluation can predict risks based on the customers' input data. This can be instant and thus reflects real time data, instead of solely relying on historical records and individual experience. In banking, AI is mainly used for a limited number of back-end applications, for example, stock forecasting and credit card ratings (Jadhav et al., 2016). In addition, Kianfar et al. (2010) demonstrated that artificial intelligence can objectively and fairly assess a customer's background, personal assets, and credit without unnecessary risk to the bank from personal emotions. Furthermore, Königstorfer and Thalmann (2020) argued that AI can help banks reduce losses from customers failing to repay loans, improve the security of processing payments, reduce labour costs by automating work, and enable apparent customer targeting. Also, in their research, Königstorfer and Thalmann (2020) showed that AI had a significant impact from technical and commercial perspectives. AI in retail banking enables more accurate predictions for previously unused data types and allows customer data to be analysed through new algorithms. Importantly, it can accurately assess credit risk and reduce banks' losses from lending and credit cards. Mhlanga (2021) reported that credit risk is essential for banking and finance. Banks need to analyse and assess the likelihood of recovering funds when granting loans to avoid unnecessary losses. When a bank contributes a loan, the financial institution should assess the borrower's current and historical financial status. Mhlanga (2021) also agreed that AI can help banks and the financial sector assess customers' behaviour and subsequently verify their ability to repay the loan. Therefore, AI improves credit decisions and identifies potential threats to which financial institutions may be exposed to.

Finally, AI can help reduce the cost of implementing accurate credit evaluation in a large-scale market. AI can be applied on the cloud, which allows customers to enquire about the service via the Internet. Therefore, they no longer rely on face-to-face meetings in branches nor managers and controllers' individual experience and judgement. Stoughton et al. (2011) found that the use of AI advisors in the financial industry has a lower and more transparent cost structure as it can help the industry reduce human costs. Furthermore, AI advisors do not create conflicts of interest with clients. This view was supported by Bolton et al. (2007) and Linnainmaa et al. (2021), who determined that when human financial advisors 9 experience conflicts of interest, there is an impact on financial advice and quality. Also, Uhl et al. (2018) agreed that AI financial advisors have higher usability, time efficiency, and cost less than human financial advisors. Woodyard and Grable (2018). suggested that the most significant advantage of AI advisors is their cost-effectiveness. When the results analysed by AI meet the needs of banks and clients, then acceptance of AI increases. This view is corroborated by Uhl and Rohner (2018). AI can also help human finance and clients reduce their behavioural biases. Similarly, D'Acunto et al. (2019) agreed that AI advisors could help the financial industry mitigate investment bias, neutrally evaluate risk levels, and predict the future. Furthermore, Wamba-Taguimdje et al. (2020) determined that AI could cover an organisation's entire value chain by improving business processes and making them more efficient, less costly, and more responsive.

2.3 Potential limitations of AI applications in credit evaluation

The limitation of AI in banking and finance are analysed from two perspectives: the inability of AI to take responsibility and the inability of AI to consider customer sentiment and behavioural issues. Fein (2015) commented that the outcome of financial decisions made by artificial intelligence advisors is not subject to human interference and financial institutions are unable to reward, punish or award penalties. This means that when a member of staff comes to the wrong investment or credit rating conclusion as an analyst, they must take responsibility. However, when an AI's system is flawed, the AI cannot be held accountable, thus increasing the risk encountered by financial institution. In a study conducted by Phoon and Koh (2017), they argued that AI does not have human intervention in its work. Therefore, AI advisors do not take care of their client's emotional and behavioural issues when analysing their situation. The lack of ability to consult and express opinions may lead to mistrust and bias on the client's part.

3. Conclusions

In conclusion, the potential contributions of AI towards credit evaluation can be articulated as follows. Firstly, AI can effectively help banks and financial markets to hedge their risks. Through standardised data (debt, age, available resources, liquidity, etc.), customer credit ratings can be analysed without interference. This can help reduce losses incurred by banks. Secondly, AI can rationalise the customer's needs (risk appetite, family situation, short and long-term investment objectives, etc.) and propose suitable solutions. Finally, AI can help reduce human costs in the financial sector through a lower and more transparent cost structure. Since AI does not have a conflict of interest with the customer, it can reduce behavioural bias and thus lead to sound advice and evaluation.

However, the limitations of a client's emotional and behavioural issues should not be neglected, which can result in the AI not wholly understanding the customer. Firstly, when the AI cannot recognise the customer's emotions and behaviours, errors can occur in the analysis results. Secondly, AI cannot be held accountable. Although AI from extensive data collation and summarisation, banks or financial institutions cannot be held accountable if AI makes mistakes or errors in decision-making, this leads to losses for the customer, the bank, or the financial institution. Notably, this research does not incorporate empirical evidence other than reviewing prior studies. Further research, based on empirical data collected from real business scenarios, is recommended to examine the conclusions from this study.

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