Risk and Regulatory Outlook 2021

Key developments in Southeast Asia: Use of artificial intelligence, machine learning and alternative data in credit decisioning

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Use of artificial intelligence, machine learning and alternative data in credit decisioning

Overview

Traditionally, credit information is obtained from credit agencies or through customer questionnaires. Subsequently it is used to assess the customer's expected credit risk through an existing credit scoring model.

These existing credit scoring models are typically developed as statistical models, using regression and decision trees techniques. Given its static nature, and the use of backward-looking information, this traditional assessment approach may not be able to completely capture the most recent or relevant customer information.

Today, financial institutions (FIs) are increasingly using alternative credit decisioning models by exploring new methods or data sources to evaluate the creditworthiness of individuals and institutions. For instance, there is increased use of artificial intelligence (AI) and machine learning (ML) techniques to perform predictive modelling or to analyse patterns in multi-dimensional data.

There has also been an increase in use of unconventional alternative data sources, such as behavioural data collected from digital platforms and applications to support credit decisions. The combined use of AI/ML models and alternative data sources has spurred the development of much sophisticated credit scoring approaches.

The adoption of AI/ML models and alternative data sources have enabled FIs to enhance the **accuracy, scalability** and **efficiency** of their credit decisioning processes.

1

Accuracy

Improved risk assessment through the use of alternative data and methodology, to complement traditional approaches

- **The right data:** FIs can better utilise existing data points and more readily incorporate new data points. These can be unconventional data or publicly available data, such as the identification of applicable adverse news that could help identify early warning signals for credit risk management. The development of business-to-customer models can leverage the computational power of AI/ML models and diverse sources of available data. This can provide a more complete understanding of a household's financial needs, increasing the accuracy of underwriting. By using a combination of available historical and current data, the FIs can perform predictions that are more unbiased, reliable and accurate.

- **Improved risk assessment:** The use of alternative methods can be complemented with traditional models to improve the accuracy of credit risk assessment, given its ability to leverage a wider range of data and various types of ML algorithms. With continued modelling results gathering and monitoring, these models can also recalibrate independently and uncover new patterns to further improve the accuracy for credit decisioning.

2

Scalability

The evolution, led by scaling up of the lending models, helps transform existing models, enabling them to better forecast future credit needs

- **Scalability and flexibility:** FIs need to evolve their lending criteria together with industry developments, potentially through extending these alternative models implemented as a future-proof platform for lending. Alternative data can be used in addition to the existing channels to unlock the potential of client segments with limited traditional credit information.

- **Anticipate credit needs:** ML approaches can be used to forecast future credit needs by analysing credit line usage and identifying historical data patterns. This would enable FIs to have early insights on where to take proactive action. It can identify customers predicted to have large expenditures at a certain time of the month using historical data and trends, who may require additional credit. FIs can then provide a tailored and targeted approach to meet their customers' needs.

- **Transform traditional models:** The usage of alternative data and credit scoring models can help expand a bank's target market to previously unbanked populations through leveraging other available data points, enabling new lending models and achieving better financial inclusion.

3

Efficiency

Automation boosts the reliability of results by streamlining existing manual processes

- **Reporting excellence:** Automation of repetitive and tedious manual tasks can help reduce the risk of human error, thereby increasing the reliability of the results. It would also help reduce the risk of human error, thereby increasing the reliability of the results.

- **Automated integration:** Manual data ingestion and transformation could be reduced significantly with automated integration across the whole credit risk management cycle. The approval and disbursements could be automated through real-time decisioning, using alternative credit scoring models to assess the credit worthiness of obligors and the availability of multiple channels for loan disbursement.

While there are numerous benefits to FIs as noted above, there are also several challenges when AI and ML are used in credit decisioning, such as the need to address regulatory and ethical concerns. We have also highlighted the other challenges in this publications and have suggested ways to mitigate them in our recommendations below.

Regional regulatory developments

Regulatory requirements, specifically on the use of alternative credit models, tools and data for decisioning, in Southeast Asia (SEA) is largely still under development. In Singapore however, there is a high adoption rate of AI/ML across industries, including FIs, which has led to an increased focus in creating and implementing regulatory frameworks. For instance, the Monetary Authority of Singapore (MAS) published an information paper on the responsible use of AI and data analytics[1] in 2018. In addition, in January 2020, the Infocomm Media Development Authority revised its second edition of the Model AI Governance Framework at the 2020 World Economic Forum, which seeks to promote trust in AI and understanding of the use of AI[2].

It should however be noted that these frameworks are not legally enforceable and merely serve as a guide for organisations that are intending or have already adopted the use of AI/ML in their ordinary course of business.

It is important to note that while there are limited regulations today in this area globally, there is a growing trend amongst SEA regulators to introduce national strategies to promote the development and usage of these alternative approaches.

[1] MAS, "Principles to Promote Fairness, Ethics, Accountability and Transparency (FEAT) in the Use of Artificial Intelligence and Data Analytics in Singapore's Financial Sector", 2019.
[2] IMDA, "Artificial Intelligence", 2021.

Regional industry observations

Across SEA, governments are spearheading the adoption of AI/ML with the launch of national roadmaps. They aim to help FIs embed these tools in their organisational infrastructure and business processes. Governments and corporations affirm the potential that such tools can bring to their businesses and the wider economies. Below are some examples of nationwide initiatives implemented to raise awareness and encourage the usage of these tools in various industries. The examples, including those beyond credit risk functions, serve as a reference for possible adoptions of AI/ML tools in the credit risk space.

Singapore

The Smart Nation and Digital Government Office, a government agency in Singapore responsible for planning Singapore's progress towards being a Smart Nation, has developed the National Artificial Intelligence (AI) Strategy that details the plans to increase the nation's adoption of AI[3].

Vietnam

The Prime Minister has reaffirmed the need for Vietnam to improve its capacity to access Industry 4.0[6], particularly the AI pillar that is expected to fundamentally change the way things are produced in the world. As a result, a legal framework and AI development policies are being gradually built and implemented in practice.

Philippines

The Philippine government is crafting an AI roadmap to improve the country's productivity and economic growth[4]. An AI task force of seven government agencies, including the Department of Trade and Industry, was formed for this initiative as it affects several industries. The Philippine Government is targeting to implement the roadmap in 2021.

Thailand

The Electronic Government Agency has developed the Thailand Digital Government Plan with an objective to digitalise Thai government agencies, which includes the use of AI. The Bank of Thailand, has also started initiatives to develop and leverage these AI/ML learning tools across a range of functions[7].

Malaysia

The Malaysia Digital Economy Corporation (MDEC), a government agency, is in the process of developing a national framework that would help streamline the nation's agenda on the use of AI[5].

Indonesia

The Indonesian government has introduced a national strategy for developing AI spanning the next 25 years (till 2045). Regulations in the country are still largely centred around the area of data protection and privacy instead of the explainability of the models used in credit scoring.

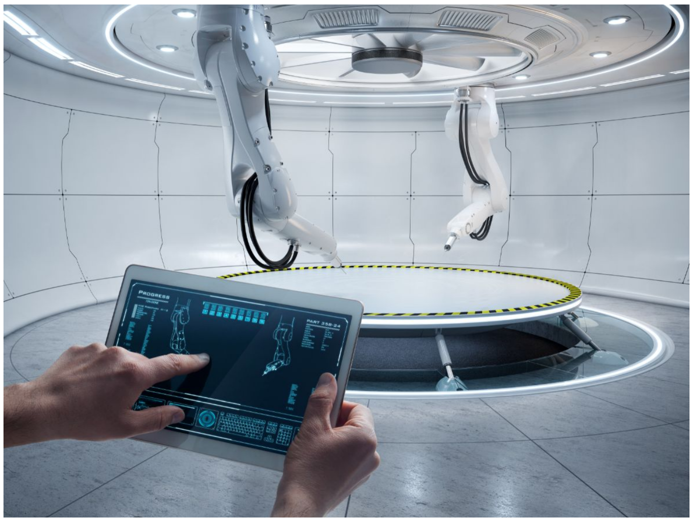
[3] SNDGO, "National AI Strategy: The next key frontier of Singapore's Smart Nation Journey", 2020.
[4] Philippine News Agency, "Gov't Crafting AI Road Map to Improve PH Productivity", 2019.
[5] MDEC, "Government, Public Policy, and Sustainable Business", 2019.
[6] Vietnam Economic Times, "Vietnam Sets Out Plans for Industry 4.0", 2017
[7] Central Banking, "Artificial Intelligence Initiative: Bank of Thailand", 2020.

Outlook for 2021 and recommendations

Outlook #1: Increasing explainability of AI/ML models

Given the increasing popularity of AI/ML approaches, the level of adoption could be a differentiating factor for lenders when conducting credit quality assessments and decision making. While there are many components to these tools, we envision that a greater focus will be placed on understanding the interpretability of the model. This is especially crucial as we live in a world where many FIs perform a systemic role in the economy, and therefore explainability of their business practices is a requirement in the industry. The use of AI/ML in credit decisioning models currently limits explainability due to the black box conundrum. Traits such as fairness, privacy, reliability and causality are difficult to capture appropriately by AI/ML when decisions are made. Given the challenges explaining these models and how they inform management decisions, there is currently limited applicability in areas such as provisioning or capital.

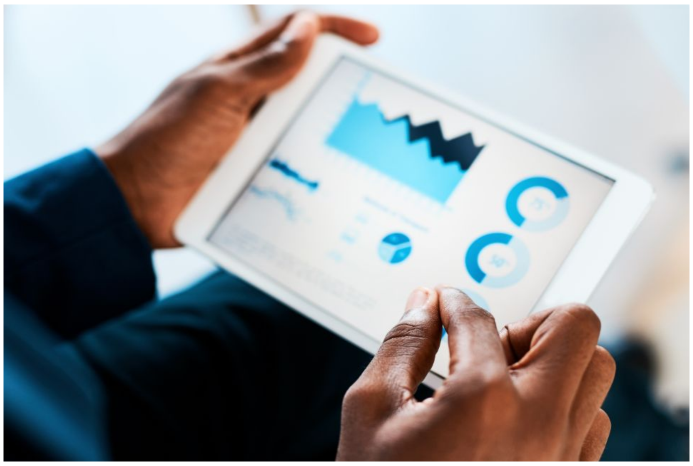
Recommendations: FIs can consider incorporating the use of model-agnostic interpretation methods into their business process, which involves separating the explanations from the ML model. This allows FIs to make use of ML models by allowing for contrastive explanations. Instead of comparing a prediction to the average prediction of the entire dataset, a comparison can be made to a subset or even a single data point. This will help provide an explanation with a reasonable foundation in outlining the various factors that led to a decision by AI/ML in a credit scoring model. FIs can also consider using these AI/ML models as “challenger models” as a check against, or even to supplement, the results produced by the existing models.



Outlook #2: Data quality will continue to be an important factor for AI/ML models

While the sources of data for both traditional and alternative scoring models are different in nature, the importance of data quality cannot be underestimated. AI/ML models tend to be more data-sensitive and require sufficiently large and comprehensive datasets in order to be trained appropriately. The results of the decisions made by AI/ML in credit scoring are dependent on the quality of the data used. As these models tend to be more automated, erroneous or biased data may not be identified and therefore incorrectly included in the models, resulting in decisions that could be misleading or compromising the overall decision-making process. In addition, AI/ML models tend to be more difficult to explain and interpret, which ultimately makes it challenging to set appropriate reasonability checks on the results obtained.

Recommendations: FIs should ensure their AI model’s risk management includes data risk as a separate dimension of risk in the model risk evaluation process. In this way, there is a proper process of addressing the data risks posed and ensures that these risks are in compliance with existing data regulations. The model risk management process should also incorporate manual checks that would be found in traditional model recalibrations, such as reconciling data and comparing model outputs with past results, to ensure that the results obtained are in line with expectations.



Outlook #3: Increased scrutiny over alternative data sources and its usage

Use of big data in ordinary business in the region will continue to increase, as evident in the government agencies' efforts in developing the respective national roadmaps and strategies. Despite the emergence of credit scoring companies utilising alternative data in recent times, there are limited regulations at present. As a result, we expect increased scrutiny from regulators in the near future as more industry players start leveraging these data sources.

Recommendations: Together with AI/ML, FIs can build more comprehensive risk assessment models that use unconventional data to support credit decisions. Unconventional data is specific to each application scenario. For instance, mobile phone data, online social data/ the Internet of Things, e-commerce transaction behaviour, utility payment behaviours and consumer lending data. These unconventional data can help identify low-risk and high-risk customers through analysis of payment behaviours, or provide current and future information for qualitative assessment of borrowers. We believe that the use of additional customer data for credit assessments can help strengthen the existing risk management strategies.

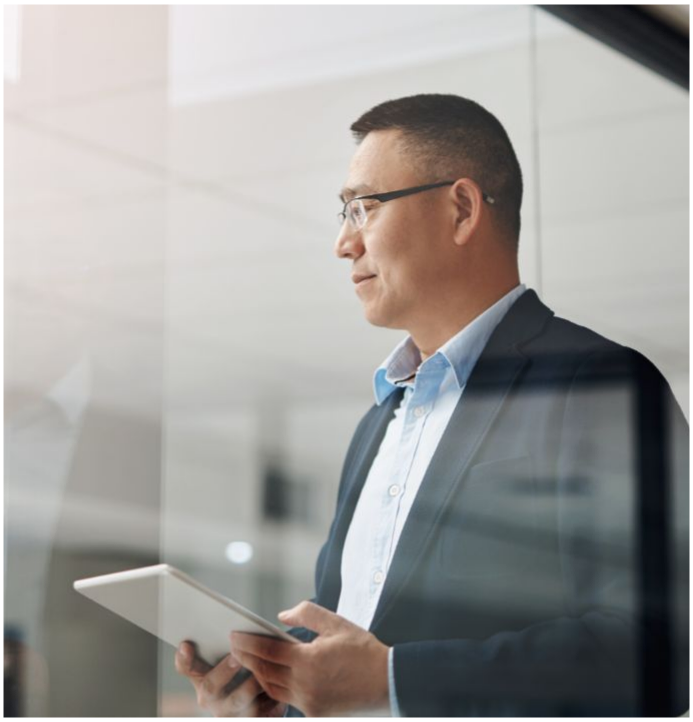
Given the novelty of unconventional data, users should also ensure that there is proper data governance in place, to confirm the usability and integrity of the data before they are incorporated into the models. It is also essential to ensure the accuracy and reliability of the underlying source to understand whether any limitations or inherent errors exist in the data, before incorporating these into the credit risk models.

Outlook #4: Ethical considerations will become more pertinent

The decision to whom loans should be granted may be exposed to the risk of bias, through differentiating credit risk based on characteristics, such as race, gender and sexual orientation. This is because much of the data fed to the machines are often biased in nature. If a biased set of historical data is used to train the AI/ML model, the resulting algorithms would carry the same bias. Where the biases are not corrected, prejudice in credit decisions may continue to permeate, causing wealth inequalities.

Recommendations: When AI/ML models are being built, inherent data biases should be removed to prevent false inferences and errors. Harvard Business Review's article "AI Can Make Bank Loans More Fair" mentions that samples of loan data for women are usually smaller compared to men, ceteris paribus, as FIs have approved fewer and smaller loans to the former in recent decades[8]. This has knock-on effects on how algorithms are built based on the data provided and subsequently on how the data is interpreted for female applicants.

With AI/ML, FIs should use these tools to identify and correct the patterns where inequalities are pervasive in the raw data. Checks can also be modelled into place to ensure that protected classes are not treated differently.



[8] Harvard Business Review, "AI Can Make Bank Loans More Fair", 2020.

Conclusion

Over the past decade, the use of alternative models and data have disrupted the industry's existing credit risk processes. While these developments bring benefits such as increased efficiency, accuracy and better risk management, there are a number of associated challenges that FIs should be aware of when implementing them. There will also be increased scrutiny around the use of these tools as more regulations develop globally. There is a clear need to stay ahead of trends - while understanding the limitations of these approaches - to avoid being left behind when these tools and alternatives are more widely adopted.

"While we expect increased regulatory scrutiny and a focus on ethical considerations in the use of AI/ML models, the potential benefits are significant, and hence FIs should have a clear plan for incorporating alternative risk models in their credit decisioning processes."

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