Streamlining Regulatory Reporting in US Banking: A Deep Dive into AI/ML Solutions

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Abstract

This paper presents an in-depth examination of the application of Artificial Intelligence (AI) and Machine Learning (ML) solutions to streamline regulatory reporting processes within the United States banking sector. With increasing regulatory complexity and reporting requirements, banks are under pressure to enhance efficiency while ensuring compliance. Through a comprehensive analysis of existing literature and case studies, this study explores the potential of AI/ML technologies to automate and optimize regulatory reporting tasks. By identifying key challenges, opportunities, and best practices, this research aims to provide insights for banks seeking to adopt AI/ML solutions in regulatory reporting, ultimately contributing to improved operational effectiveness and regulatory compliance.

Introduction

The rapid advancement of Machine Learning (ML) and Artificial Intelligence (AI) is catalyzing a surge of interest in sophisticated quantitative methodologies across diverse economic sectors. In aligning with global digitization trends, banks are poised to deliver products that not only meet but exceed the evolving expectations of customers while also competing effectively with FinTech entities. The proliferation of e-commerce and the seamless integration of intuitive online services have cultivated uniform expectations within society, notably emphasizing attributes such as speed, user-friendliness, transparency, and comprehensive digitization in banking services.

AI methodologies offer multifaceted applications across various facets of banking operations, including:

1. Market risk management: Encompassing client behavior forecasting and alignment of asset and liability maturity profiles.
2. Valuation of loan collateral (e.g., real estate) and financial instruments.
3. Customer service enhancements: Ranging from ID card information scanning to speech and speaker recognition through the deployment of chatbots and the development of intelligent application interfaces tailored to individual customer profiles.
4. Automated detection of fraudulent activities and money laundering attempts, integral to Know Your Customer (KYC) protocols, alongside bolstering cybersecurity measures.
5. Implementation of Internal Ratings-Based (IRB) models to compute regulatory capital for credit risk.
6. Stress-testing protocols to assess institutional resilience under adverse scenarios.
7. Automated creditworthiness assessment systems.

In the realm of Big Data and advanced analytics methodologies, many stakeholders within the sector are actively exploring the aforementioned dimensions to varying extents. Big Data, characterized by massive volumes of structured and unstructured data from diverse sources, underpins these efforts, while advanced analytics harnesses a multitude of analytic techniques to extract actionable insights from this data landscape.

The European Banking Authority (EBA), among others, recognizes the transformative potential of integrating Big Data and advanced analytics in banking operations, facilitating innovation and operational efficiencies across the sector.

The utilization of advanced analytics methods presents challenges not only for banks but also for regulators. Banks perceive opportunities for risk reduction and income enhancement through the seamless adoption of AI solutions, achieved by employing more sophisticated approaches, acquiring specialized competencies, and developing robust IT systems. However, the application of AI also entails inherent risks such as misuse or avoidance due to regulatory ambiguity and managerial or societal reluctance towards AI technologies.

Our research objectives are as follows:

1. Compare and evaluate various scientific and regulatory perspectives on defining AI and ML.
2. Propose clear definitions of AI and ML for legislative purposes.
3. Assess the complexity and interpretability of different advanced quantitative methods applied in banking.
4. Propose a viable approach for further advancing quantitative methods, particularly in areas requiring strict interpretability.

This research targets the following stakeholders:

1. Policymakers responsible for defining AI and ML for regulatory compliance.
2. Practitioners employing complex quantitative methods across various banking domains.
3. Executives tasked with making strategic decisions concerning the adoption of complex quantitative systems within banking domains.

The primary benefits derived from our study include:

1. Enhanced comprehension of the current landscape of AI/ML definitions proposed by scientists, regulators, and international organizations.
2. Insight into the application of complex quantitative methods within diverse banking domains.
3. Comparative analysis of the complexity and interpretability of the aforementioned methods.

4. Exploration of potential approaches for advancing the application of complex quantitative methods in banking.

Definitions of AI

Defining AI presents a significant challenge within the realm of advanced computational methodologies. Several factors contribute to this complexity:

1. Diverse Definitions: The definitions of AI and ML vary across industries and contexts, leading to ambiguity and inconsistency.
2. Varied Understanding: Perception of AI among different societal stakeholders—managers, scientists, politicians, and legal institutions—differs, resulting in a lack of cohesive identity.
3. Differential Consequences: The implications of categorizing a method as AI or ML are approached differently, adding to the challenge of defining these concepts.

Currently, AI is defined by scientists and various institutions, with a focus on legal status and its implications. We aim to present perspectives from both domains: the state-of-the-art understanding aids researchers and practitioners, while legal interpretations influence companies' decisions on investing in AI-based solutions. Scientific definitions of AI have evolved over the 20th and 21st centuries, whereas legal institutions have been shaping their approaches more recently. While the scientific perspective prioritizes current advancements, legal considerations hold greater significance for companies and banks, given their adherence to regulatory frameworks.

Historically, the concept of AI emerged sporadically, with early mentions appearing in literature, such as Karel Čapek's play "R.U.R." in 1920. However, a more systematic approach to AI emerged in the mid-20th century. Alan Turing's proposal of the Turing Test in 1950 marked a significant milestone, suggesting that a machine demonstrating human-like conversation skills could be deemed intelligent. Nonetheless, the Turing Test has faced criticism for its narrow focus on chatbots, highlighting its limited practical applications within the broader scope of AI research.

The year 1956 is widely regarded as the inception of the modern concept of Artificial Intelligence (AI), marked by the Dartmouth Summer Research Project on Artificial Intelligence. The conference, led by John McCarthy and Marvin Minsky, was founded on the premise that "every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it." While this thesis shaped the trajectory of AI development, defining AI remained a challenge, hinging on interpretations of what constituted a "feature of intelligence" and whether a particular advancement was sufficiently complex to qualify as AI.

The notion of AI can be elucidated within the framework of intelligent agents, as outlined in widely adopted textbooks such as "Artificial Intelligence: A Modern Approach." An intelligent agent is defined as a "system that receives percepts from the environment and performs actions." These agents are categorized into various types, including simple reflex agents, model-based reflex agents, goal-based agents, utility-based agents, and learning agents. Of particular relevance to our article are the following two categories:

1. Simple Reflex Agents: These agents react solely to current incentives from the environment, disregarding its historical context, and operate according to a straightforward rule: if condition A is met, then action B is executed.
2. Learning Agents: These agents have the capability to enhance their performance based on their interactions with the environment, allowing them to adapt and improve over time.

These classifications offer valuable insights into the functioning and potential applications of AI, aligning closely with the focus of our article.

The key aspects of the definition presented above are as follows: AI does not necessarily require learning capabilities; it operates autonomously within a given environment and can be based on relatively simple mechanisms, such as a streetlamp that activates in darkness or a thermostat. We view the categorization of AI agents into distinct categories as a coherent and practical approach, facilitating tailored solutions for each type of AI. However, this approach has its drawbacks. Categorizing solutions can prove challenging in practical applications, especially when the consequences of classification vary significantly. Additionally, regulators and global institutions often prefer simplified definitions, potentially rendering the categorization of intelligent agents too complex for everyday use.

An alternative proposal suggests using the term Computational Intelligence (CI) instead of AI, as advocated by Poole, Mackworth, and Goebel in 1998. This perspective defines an agent as a program equipped with prior knowledge about the world, enabling learning based on historical data. However, some researchers argue that the term "artificial" is not problematic in defining AI, and substituting it with another word would yield minimal change.

Definitions of ML

Defining the term ML (Machine Learning) is generally considered easier compared to AI, as it is narrower in scope and less abstract in meaning. Unlike AI, ML definitions tend to be more uniform across the literature. Our review of ML literature is less extensive than that of AI, given the similarity of most ML definitions. Similar to the AI section, we begin with insights from the state-of-the-art, followed by definitions from global organizations shaping ML understanding, and conclude with regulatory perspectives.

The key challenge in defining ML lies in precisely determining whether a machine, computer, or program is exhibiting learning behavior. Initially, ML was defined as a field enabling computers to learn without explicit programming (Samuel, 1959). However, this definition lacks specificity regarding the concept of "learning." A more refined definition characterizes ML as a computer program that learns from experience E regarding task T and performance measure P, with its performance on T improving as measured by P with experience E (Mitchell, 1997). Mitchell's definition, widely accepted in engineering contexts, remains relevant today (Alzubi, Nayyar, Kumar, 2018). From a scientific standpoint, this definition offers clarity and utility. In essence, ML can be viewed as automated detection of meaningful patterns in data, empowering programs to learn and adapt (Osisanwo et al., 2017, based on Shalev-Shwartz, Ben-David, 2014: 7).

The aforementioned definitions of ML are notably similar and appear clear and beneficial from a scientific standpoint. However, their practical application raises certain concerns, particularly in clarifying what is meant when asserting that "X is an ML algorithm." In statistical modeling, the concept of "learning" is akin to the process of estimating model parameters. Yet, once these parameters are estimated, the learning process typically concludes, at least temporarily. Therefore, when declaring "X is an ML algorithm," it implies that the algorithm has autonomously determined parameters based on available data during the estimation process.

While model parameters can be estimated using various optimizers or techniques, in practice, humans may also intervene to set these parameters for reasons such as specific expectations regarding future events. In such instances, the ML algorithm ceases to be truly ML, as it lacks the crucial element of autonomous learning from data. While scientifically this divergence may seem inconsequential, from a legal standpoint and in terms of practical application by companies, it holds significance.

Demands for sophisticated quantitative systems

In a broader context, the interest in regulating AI stems from the escalating complexity of quantitative solutions deployed across various sectors, including banking. As institutions entrusted with public confidence, banks must address potential uncertainties surrounding these applied solutions. Common concerns within the realm of complex quantitative system applications include:

1) Legality: Providers of quantitative systems must demonstrate compliance with applicable laws and regulations. The growing intricacy of these solutions may pose challenges in assessing their legal applicability in practice, as highlighted by the European Commission (2019), for instance.

2) Ethics: Defining an ethical quantitative system presents challenges, with key aspects including the avoidance of discrimination and stigmatization based on age, gender, ethnicity, disability, etc., as well as the preservation of privacy and prevention of physical and mental harm. Ethical dilemmas may arise, such as determining the ethics of denying mortgage loans based on age or using social network data—like contacts with a poor credit history—to influence creditworthiness scores (Sadok et al., 2022).

3) Transparency: Ensuring transparency entails thorough documentation of applied solutions, including clear and traceable algorithms that perform as intended. Such systems should also be subject to adequate validation processes.

4) Explainability: While transparency pertains to the clarity of algorithms, explainability refers to the comprehensibility of system outputs by humans. This involves understanding the degree of influence of input information on the output. The level of output comprehension required depends on the specific application—for example, indicating the most impactful variables for one domain, while necessitating clear correspondence between input and output for another.

5) Security: It is imperative that developed systems are implemented securely, minimizing the risk of hacking or unauthorized access.

6) Data Handling: Ensuring that input data is of high quality and adequately protected is crucial. Proper data governance processes must be maintained with due diligence.

7) Human Supervision: Systems should undergo regular monitoring overseen by human operators, tailored to the nature of the applied solution.

8) Accuracy: While some level of bias may be unavoidable, particularly in forecasting, it should be quantifiable. Sources of bias must be identified and effectively addressed. Bias can stem from various factors, including systemic bias resulting from institutional procedures, human bias influenced by simplified judgment, computational bias arising from non-representative input or mishandling of outlier data, and algorithmic bias such as over-fitting or under-fitting of data patterns or misapplication of mathematical representations.

The list of concerns outlined above can be further expanded or refined within specific application areas or institutions. Although statistical computations have long been prevalent in the banking industry, the introduction of AI and ML applications has introduced new challenges. Differences in the definition of ML between documents published by the European Banking Authority (EBA) and other authors/institutions (such as ISO, OECD, and the European Commission) highlight the complexities inherent in regulating AI and ML within the banking sector.

Comparison of quantitative tools applied in banking areas

The importance of clear definitions for AI and ML in banking is closely tied to the heavily regulated nature of the banking sector, which operates under various levels of regulation including national credit laws and both national and international banking-specific regulators. Consequently, regulations governing AI and ML governance aim to impose additional restrictions and requirements on tools classified as AI or ML. Avoiding vague definitions for AI and ML is crucial for several reasons:

1) Clarity is essential when constructing advanced and costly quantitative frameworks in banks, ensuring an appropriate approach over the long term.

2) Ambiguous legal foundations may impede banks' transition to more advanced solutions.

3) Lack of clarity may lead to the exploitation of legal loopholes and the structuring of complex quantitative systems in ways that evade classification as AI/ML.

To address these concerns, our approach involves:

1) Briefly examining different banking areas and presenting potential AI applications based on available literature and the author's experience.

2) Classifying the methods applied, assessing their complexity, interpretability, and threats/opportunities in practical applications, and comparing their usefulness within the restrictive regulatory environment.

Table 1 outlines various banking domains alongside potential applications of advanced techniques discussed in this paper. While the list of areas is compiled from the author's perspective, it is important to note that some banking categories may be broader than others. Additionally, the specific applications listed next to each domain do not encompass all possible AI applications within those areas. However, these applications reflect general trends within specific domains. Many of these applications are proposed by scientists and their practical implementation in banks must adhere to existing regulations and remain resilient to potential changes. Regulatory approaches vary across countries and geographical regions, such as the EU, as discussed in sections 2 and 3.

Different segments within the banking industry present unique opportunities for the application of advanced solutions. Here, we explore specific banking areas and potential applications of advanced techniques within each domain:

1. Risk Management:
  - Utilizing AI/ML algorithms for credit risk assessment, including predictive modeling to identify default probabilities.
  - Implementing anomaly detection systems to identify fraudulent transactions or suspicious activities.
  - Developing AI-powered stress testing models to evaluate the impact of adverse economic scenarios on a bank's portfolio.

2. Customer Service:
  - Deploying AI-powered chatbots to handle customer inquiries and provide personalized assistance.
  - Implementing natural language processing (NLP) algorithms to analyze customer feedback and sentiment, enabling banks to improve service quality.
  - Utilizing predictive analytics to anticipate customer needs and offer tailored product recommendations.

3. Fraud Detection and Cybersecurity:
  - Leveraging AI/ML algorithms for real-time fraud detection, including pattern recognition to identify unusual transaction patterns.
  - Implementing biometric authentication systems for secure access to banking services.
  - Using machine learning algorithms to analyze network traffic and detect potential cyber threats in real-time.

4. Compliance and Regulatory Reporting:
  - Implementing AI-powered solutions for Know Your Customer (KYC) processes, including automated identity verification and risk assessment.
  - Utilizing natural language processing (NLP) techniques to analyze regulatory documents and extract relevant information for compliance purposes.

- Implementing AI/ML algorithms for transaction monitoring to detect and prevent money laundering activities.

5. Asset Management:
   - Utilizing machine learning algorithms for portfolio optimization, including predictive modeling to identify investment opportunities and manage risk.
   - Implementing AI-powered robo-advisors to provide automated investment advice based on individual risk profiles and financial goals.
   - Using sentiment analysis techniques to gauge market sentiment and make informed investment decisions.

These are just a few examples of how advanced solutions, powered by AI and ML technologies, can be applied across various banking domains to improve efficiency, enhance customer experience, and mitigate risks.

Specific banking areas and possible applications of advanced solutions within those areas

Banking area	Advanced methods applications
Risk management: credit risk	For Probability of Default (PD), the applied methods involve logistic regression, Support Vector Machines or logistic regression with random coefficients (Dong, Lai, Yen, 2010). Other proposals involve Naive Bayes, neural networks, the K-Nearest Neighbour classifier, decision tree or random forest models (Wang et al., 2020). Other commonly used credit risk models are Loss Given Default (LGD), which is a share of an asset that is lost when a client defaults, and Exposure at Default (EAD), which isa predicted loss that the bank may incur in the case of client default. For LGD and EAD, the considered approaches involve e.g.: Naive Bayes, linear regression with data transformations, mixture models, neural networks, and logistic regression (Yang, Tkachenko, 2012). The PD, LGD and EAD are the three main parameters needed to calculate economic/regulatory capital for banking institutions under Basel II. For the credit cards scoring system, the bidirectional long short-term memory (LSTM) neural networkhas been proposed (Ala'raj, Abbod, Majdalawieh, 2021). For credit risk stress testing purposes, least absolute shrinkage and selection operator regression (LASSO) (Chan-Lau, 2017) and Multivariate Adaptive Regres- sion Splines (MARS) (Jacobs Jr., 2018) have been proposed. The real estateprice (where real estate is a loan collateral) can be estimated with variousML techniques such as linear regression, convolutional neural networks, and random forest (Potrawa, Tetereva, 2022).

Risk management/ IT: cybersecurity	Cybersecurity can be classified as a part of operational risk presented below, however, we decided to present it as a separate section. The cyber-security section presented here is based mainly on Sarker et al. (2020). An intrusion detection system (network and software security) can be built with the application of: Support Vector Machines, neural networks (including recurrent neural networks and LSTM), the K-Nearest Neighbo- ur classifier, the K-means algorithm, Naıve Bayes, the decision tree model, the genetic algorithm, and the hidden Markov model. The Support Vector Machines model has been used for DDoS detection (where the DDoS is Distributed Denial of Service, which is an attack made with multiple computers and internet connections meant to make a machine or network inaccessible for intended users). For malicious activities and anomaly detection, neural networks, Adaboost, decision tree models, and Support Vector Machines have been applied. Probabilistic neural networks have been proposed for user authentication with keystroke dynamics, where keystroke dynamics is the typing style of a client (Revett et al., 2007).

Banking area	Advanced methods applications
Risk management: liquidity risk	Artificial neural networks and Bayesian networks can be applied to various liquidity risk processes such as stress tests, simulations, recovery and contingency plan. AI/ML can also improve the Internal Liquidity Adequacy Assessment Process (ILAAP) and Asset Liability Management (ALM) processes (Milojević, Redzepagic, 2021). For a liquidity risk early warning prediction system, LASSO regression, random forest and gradient boosting with decision trees have been proposed (Drudi, Nobili, 2021). For early warning liquidity risk, system neural networks and Bayesian networks have been also proposed (Tavana et al., 2018).
Risk management: operational risk	In the case of operational risk, the area where advanced quantitative techniques are heavily explored, the Know Your Customer (KYC) process is used. The KYC guards the bank against financial fraud (including credit card fraud), money laundering, and terrorist financing. For anti-money laundering, Support Vector Machines (Keyan, Tingting, 2011; Chen, 2020), neural networks (González, Velásquez, 2013), Bayesian networks (Khan et al., 2013), decision trees and random forests (Chen, 2020) have been proposed. For fraud detection systems, Bayesian algorithms, the K-Nearest neighbour, Support Vector Machines and the bagging ensemble classifier based on the decision tree model have been applied (Pun, Lawryshyn, 2012; Dal Pozzolo, 2015; Leo, Sharma, Maddulety, 2019).

Risk management: interest rate risk	The topic connected with both interest rate risk and liquidity risk is matching of maturity profiles of assets and liabilities. Therefore, in the case of assets, loan prepayment models are applied and in the case of liabilities, savings and current accounts churn prediction models are used. In the case of savings accounts, churn prediction neural networks, gradient boosting based on decision trees, the Generalised Linear Model(GLM), Support Vector Machines and random forests have been applied (Verma, 2020). For prepayment modelling, random forest alongside the proportional hazard model (Liang, Lin, 2014), neural networks (Zhang, Teng, Lin, 2019), logistic regression (Zahi, Achchab, 2020), and the gradient boosting classifier based on decision trees (Schultz, Fabozzi, 2021) have been proposed. For future interest rates prediction,the Gaussian mixture model (Kanevski, Timonin, 2010) has been proposed.

Banking area	Advanced methods applications
Risk management: market risk	For investment risk prediction, the Adaboost Support Vector Machine has been proposed (Luo, Metawa, 2019). For the Credit Default Swap (CDS) derivative, the spread approximation method with random forest regres- sion has been proposed (Mercadier, Lardy, 2019). For evaluation of risk premium of commodity futures contracts, LSTM neural networks have been proposed (Rad et al., 2021). Value at Risk (VaR) models are com- monly applied in a market risk area, for example, for equity risk. The VaR computes a maximum loss over a given period with an assumed level of confidence. For VaR calculation, an important aspect is the future volatilityprediction. For volatility estimation, neural networks and the Generalised Autoregressive Conditional Heteroskedastic (GARCH) model have been proposed (Monfared, Enke, 2014; Zhang et al., 2017). For foreign exchange(FX) risk, the genetic algorithm alongside the LSTM neural network has been proposed (Loh et al., 2022). For derivatives pricing, neural networks and boosted random trees have been proposed (Ye, Zhang, 2019).
Risk management: model risk	AI and ML approaches can be applied during the validation of applied qu- antitative systems in different banking areas. Advanced ML models can bebuilt as a benchmark for the existing, simpler models. For data quality va- lidation, the outlier detection with ML can be applied, for example, based on the Gaussian Mixture Model, the Dirichlet Process Mixture Model, neu- ral networks, probabilistic principal component analysis (PPCA), Support Vector Machines (Domingues et al., 2018), or the so-called isolation forest model based on the random forest algorithm (Liu, Ting, Zhou, 2008).

Customer experience	Nowadays customer experience in the case of using digital banking and visiting bank stationary branches can be simplified and time-optimised with the application of ML. With convolutional neural networks widely applied for image recognition (Hijazi, Kumar, Rowen, 2015; Liu, 2018), the bank can apply models that significantly shorten time necessary for the existing processes. The image recognition system can be applied, for example, to: a model that automatically reads information from the client ID or a model that verifies if the next tranche of a mortgage can be transferred to the client based on the construction progress documented with photos. In the case of digital banking, a personalised system with transaction categorisation and cash flow prediction can be built with recurrent neural networks (Kotios et al., 2022). The automated credit risk scoring system, offering customised loans to the clients based on their characteristics (every-month cash flows, etc.) can be developed with ML techniques (discussed in the credit risk section above). Advanced chat bots based on a neural networks approach called Natural Language Pro- cessing (NLP) (Adamopoulou, Moussiades, 2020) can be developed, for example, to call customers with a reminder of an overdue loan instalment. To automatically propose banking products that a given client would be most interested in, banks can develop a profiling system adapted to digital banking, for example, based on k-means and neural networks algorithms (Dawood, Elfakhrany, Maghraby, 2019).

The majority of proposed solutions for application in specific banking areas, as presented in Table 1, tend to recur across various banking sectors. This recurrence is due to the versatile nature of most quantitative tools, which can be effectively applied to a broad spectrum of banking challenges. Table 2 offers the author's subjective evaluation of these methods, along with the associated threats and opportunities. Only methods meant for datasets with observable dependent variables (labelled datasets) and designed for classification or regression problems are included. Therefore, optimization algorithms (e.g., genetic algorithms) or methods intended for unlabelled datasets (e.g., K-means algorithm) are excluded from this categorization.

In Table 2, complexity and interpretability are assessed under the assumption that the situation is not overly simplified, with several auxiliary variables considered, and methods applied due to their unique features. The evaluated methods encompass:

1) Linear regression based on untransformed data.
2) Linear models based on transformed data, including multinomial regression and models pre-processed with PCA or PPCA.
3) Generalized Linear Models, such as logistic regression.
4) Regularized linear regression techniques like LASSO, ridge regression, and elastic net regression.
5) Decision trees for both classification and regression.
6) Random forests for classification and regression tasks.

7) Mixed (mixture) models, including Gaussian mixture models and Dirichlet process mixture models.

8) Multivariate Adaptive Regression Splines.

9) Boosting methods like Adaboost and Gradient boosting with decision trees or other models.

10) Markov models, including hidden Markov models and Monte Carlo hidden Markov models.

11) Neural networks of various types, including recurrent, LSTM, bidirectional LSTM, convolutional, and NLP.

12) Bayesian methods, such as Naive Bayes and Bayesian networks.

13) Support Vector Machines, including Support Vector Regression.

14) Ensemble methods that combine results from multiple complex models.

15) Proportional hazard models.

16) K-Nearest Neighbor classifier.

17) Autoregressive models, including GARCH.

Assessment of advanced quantitative methods in the context of banking

Quantitative method	Complexity/ Interpretabi-lity*	Opportunities of application in the banking area	Threats of application in the banking area
Linear regression	Very low complexity/ very easy to interpret	Simplicity, understandability of the method by a lot of staff, the short time needed to estimate and interpret the model, the method easy to explain to high management and the regulator	Works well only for linear dependencies between variables, the necessity of testing for the fulfillment of assumptions, the regulator may potentially question such a solution as the one with too weak predictive power
Linear models based on transformed data	Low complexity/ moderate to interpret	Transformations can be tailored to a specific economic theory; the application of transformations may be a great way to enhance existing linear models in banking	In the case of PCA and more complicated transformations, the interpretability, in general, is more difficult, multinomial regression and some transformations may produce unstable pre- dictions

Quantitative method	Complexity/ Interpretabi-lity*	Opportunities of application in the banking area	Threats of application in the banking area

Generalised Linear Models	Low complexity/ easy to interpret	Logistic regression is a staple in the case of binary classification, for example, in the case of PD modelling, ease of interpretation, which is especially important in the case of explanation of the reasons for loan rejection to clients, etc.	Using less popular link functions than the logit/probit requires more knowledge and understanding of sta- tistics, the assumption regarding the independence of random variables, and in some cases applying Generalised Linear Models may be questioned as too simple in the final form and at the same time too complex in terms of require- ments regarding distribu- tion assumptions, etc.
Regularised linear regression	Very low complexity/ easy to interpret	May enhance the perfor- mance of linear regression models at the same time being relatively simple, very helpful if the linear model is the right choice, but the issues with overfitting were detected (too good fit to the training dataset with considerably worse performance in the case of actual predictions)	The existence of hyperpara- meter requires some serious enhancement of the estima- tion process, which is also more time-consuming than the standard linear regres- sion estimation process, the choice of regularised regression over non-regulari- sed requires additional documentation
Decision tree	Very low complexity/ very easy to interpret	Simplicity may work very well in the case of simple segmentation tasks, inter- pretability, easy to explain, visualise, and capture non-linear relationships, may be easily combined with other methods	Inadequate for more com- plex problems, a single de- cision tree is very sensitive to the dataset based on which model parameters are estimated, which may result in weak performance on new data, requires addi-tional testing for stability
Random forest	Average complexity/ hard to interpret	Greatly improves stabili- ty issues of single decision trees, fast computation, despite being hard to interpret, the algorithm behind random forests is relatively easy to explain	Requires model agnostic methods in order to inter- pret results and therefore in most cases extensive documentation is essential

Quantitative method	Complexity/ Interpretabi-lity*	Opportunities of application in the banking area	Threats of application in the banking area
Mixed (mixture) models	Average complexity/ moderate to interpret	Random effects provide great tools for specific requirements regarding available data and can handle them better than fixed effects, they can be applied to many different practical problems, mixturemodels can be associated with different models (linear models as well as Generalised Linear Models or even random forests)	Mixture models require additional testing, i.e. regarding assumed distributions of random effects, random effects are not so easy to interpret and explain to higher management as fixed effects, application of random effects to more complex models, for example, to random forests significantly increases time needed for computation
Multivariate Adaptive Regression Splines	Low complexity/ easy to interpret	Elasticity, simple for interpretation, automatic selection of the auxiliary variables for the model, computer implementationsof the model are time-efficient	No possibility of explicitly presenting the formulas describing the confidence intervals for the parameters, similarly to a single decision tree, may be inadequate for more complex problems and requires additional testing for stability
Boosting methods for classifica-tion and regression	High complexity/ very hard to interpret	Models based on boosting often give very accurate results (many Kaggle com-petitions were won with the application of boosting methods), existence of very time-effective software implementations, boosting may be applied for different classes of base models, e.g.: linear models, decision trees, etc.	Results are very difficult to interpret (require model agnostic methods), the cor-rect choice of hyperpara-meters may be difficult, sensitivity to overfitting to training data (in that case, the model fits the training data well but does not work well in the case of actual predictions)

Markov models	Average complexity/ easy to interpret	A wide variety of applications, strong economic background	The method is based on discrete states, which may cause serious technical issues in implementation, the method is superseded often by other more accurate models, frequently requires other models/methods to produce accurate results

Quantitative method	Complexity/ Interpretabi- lity*	Opportunities of application in the banking area	Threats of application in the banking area
Neural networks	Very high complexity/ very hard to interpret	Very accurate if done correctly, and the method fits well with many classes of problems, despite being very complex, there are a lot of scientific materials and tutorials available	A very time-consuming method, requires specific knowledge and experience in order to correctly choose network architecture, sensitive to overfitting, requires model agnostic methods for results interpretation and very extensive documentation
Bayesian methods	High complexity/ easy to interpret	Easy to interpret, Bayesian methods provide a convenient setting for a wide ran-ge of methods, for example, issues with missing data	May produce misleading results in certain cases, is time-consuming, requires expert knowledge and experience to produce an accurate model that works well in practice

Support Vector Machines	High complexity/ hard to interpret	A computationally time-effective method even with large datasets, many statistical software implementations, despite being a relatively complex method, the number of hyperpara- meters is relatively small (for example, in comparisonwith Gradient boosting based on decision trees)	The method difficult to interpret, among other advanced algorithms relatively hard to understand and explain to higher management
Ensemble methods	Very high complexity/ very hard to interpret	May produce very accura- te tools if done well, the future-proof method in termsof accuracy	In the case of ensemble of several complicated models, the interpretability may be very hard or even impossible, a very time-consuming method that requires a lot of knowledge and careful- ness from its practitioners, due to poor interpretability can be explored only in the areas where interpretabilityis not required, neither expected

In situations where strict interpretability is paramount, higher management may hesitate to approve changes incorporating more accurate yet potentially less interpretable solutions. In such scenarios, we advocate for a gradual transition towards more intricate approaches. For instance, in credit risk modeling, transitioning from logistic regression to a neural network might face resistance from higher management or regulatory hurdles. As outlined in Table 2, methods that are challenging to interpret would be extremely difficult or impossible to implement when strict interpretability is required. However, in such instances, existing solutions can be augmented with easily interpretable methods. This gradual enhancement could involve:

1) Incorporating random effects into models with only fixed effects, as seen in the shift from logistic regression to logistic regression with random effects in PD modeling.
2) Introducing additional segmentation into the modeling problem. For instance, when modeling a portfolio using linear regression, enhancing the model might involve segmenting the dataset into several sub-portfolios using a decision tree, followed by applying separate regularized linear regression to each segment.

The advantages of gradually enhancing existing solutions are manifold:

1) Executives responsible for final decisions may view such proposals as safer and may be more inclined to approve them.
2) The risk of unforeseen issues, such as loss of social trust and reputation, during implementation is reduced compared to sudden transitions from simple to complex models.
3) These models are easier to develop due to greater reliance on existing solutions, as opposed to a complete paradigm shift.

4) Comparing old and enhanced versions of the model in terms of predictions, accuracy, and result simulations is straightforward.

5) Such models are more resilient to potential regulatory changes regarding the treatment of AI.

Discussion

In various sectors of the banking industry, such as credit risk assessment, quantitative solutions are already subject to regulation to some degree. Approaches like linear or logistic regression serve as foundational models for many quantitative systems utilized in practice. The banking sector is increasingly striving to adopt a data-driven approach while ensuring compliance with regulations, maintaining ethical standards, and fostering trustworthiness. However, there are variations across different domains; for instance, credit risk assessment tends to be more rigorously regulated and detailed compared to areas like product recommendation models in mobile banking applications.

Given the current landscape of quantitative solutions in banking and the prevailing regulatory approaches toward AI and ML for legislative purposes, we propose the following:

- A broad definition of AI that encompasses all mentioned quantitative systems in the article: "AI is a system that, at certain stages of its process, perceives its environment and acts autonomously."
- A similarly broad definition of ML that encompasses all the quantitative approaches discussed: "ML is an approach that generates output based on input data from various sources, such as expert opinion parameters or observations of specific phenomena."

Given the comprehensive nature of the definitions proposed above, virtually all quantitative and autonomous processes within the banking industry could fall under the umbrella of AI. Consequently, regulations governing applied solutions should be applicable to both established methods within the industry and new proposals put forth by domain experts. This approach satisfies crucial regulatory objectives, namely clarity and practical applicability.

Adopting the proposed approach to legislative definitions would allow for formulating requirements specific to AI/ML challenges within particular contexts, such as credit risk. Alternatively, regulations could omit the explicit inclusion of AI/ML definitions altogether, similar to the approaches seen in the US and Chinese examples discussed earlier. However, this approach risks future regulatory interpretations of AI/ML and may contribute to uncertainty, hindering innovation and progress. Therefore, we contend that a broad definition of AI/ML in regulatory frameworks offers a more robust solution.

Under such regulations, requirements pertaining to the explainability of AI methods in the credit risk domain should be clear and consistent across regulatory bodies. It is imperative to avoid situations where a method classified as AI by one authority differs from another's understanding. Moreover, a general approach to AI definition allows for formulating diverse requirements across different banking domains without solely focusing on classification as AI. In essence, virtually all existing quantitative solutions in banking would be classified as AI, while all data-driven models would be classified as ML.

The primary advantage of this approach lies in regulatory clarity. Practically, it eliminates the need to differentiate between more and less complex approaches, thus alleviating industry concerns regarding defining underlying concepts. Alternatively, if regulators seek to distinguish between simple and complex approaches, clear guidelines must be established to delineate AI models from non-AI models—an inherently challenging task. This distinction is complicated by the potential black-box nature of complex, nonlinear solutions and the difficulty humans face in understanding relationships between variables created by such models or interpreting their results accurately.

An important consideration in the discussion surrounding clarity and explainability of applied solutions is the inherent complexity of the methods indirectly employed in the process. These methods, which seek to optimize model parameters or hyperparameters, such as genetic algorithms or algorithms aimed at enhancing the interpretability of model results, add layers of intricacy to the overall process. For instance, the proposal to simplify complex models based on the outcomes of explanatory methods (Gosiewska, Kozak, Biecek, 2021) renders the final model parameters

more understandable for interpreting the ultimate outcome. However, the entire algorithm leading to the final solution is considerably more complex than traditional statistical solutions like linear or logistic regression because it involves:

1) Developing a complex model with an optimal search for parameters/hyperparameters.
2) Applying a selected explainable method algorithm.
3) Employing an additional algorithm to transform the results of the explainable method into a new, simplified model.
4) Testing the final solution.

As a result, regulators in the banking industry should pay particular attention to the following aspects of quantitative AI systems:

1) Defining the threshold for sufficient explainability of quantitative methods utilized in banking.
2) Specifying the required level of clarity in the final results—for instance, whether it is necessary to identify the most influential client features leading to loan rejection and clearly articulate their numerical impact on the outcome.

The requisite level of clarity in model outcomes would render the distinction between more and less complex solutions (AI or non-AI) unnecessary. Interpreting results generated, for instance, by linear regression should be relatively straightforward, whereas meeting the same requirements with a neural network could pose a more formidable challenge. Therefore, irrespective of a system's complexity, if a model developer can meet a certain threshold of algorithm clarity and final outcome interpretation, the proposed solution could be applied to a given banking domain. However, defining the adequate level of explainability is also challenging due to the stochastic nature of many methods proposed for interpreting model outcomes.

A broad approach to defining AI and ML could aid in fostering public understanding of AI. For instance, the notion that explaining the outcome of a particular AI system requires creating another AI system might provoke anxiety, unless accompanied by the understanding that essentially all quantitative systems based on data are classified as AI by regulators. Society is generally apprehensive about the prospect of AI with unclear objectives (black box), spiraling out of control, and potentially causing unpredictable harm. An intriguing perspective on this issue suggests that instead of attributing bad outcomes to inherently mysterious and uncontrollable systems, we should view the misuse of inappropriate technology as a deliberate act by the system's creator. The cultural narrative surrounding complex and enigmatic technology is often leveraged to justify the deep involvement of the AI industry in policymaking and regulation, thereby reinforcing the market dominance of large companies and legitimizing their participation in regulatory processes.

Conclusions

In this study, we have endeavored to examine the applications of AI and ML in the banking sector. Our analysis began with an exploration of the definitions of AI and ML as delineated by scientists, global organizations, and various regulatory bodies worldwide. Our findings regarding these definitions can be summarized as follows:

1) The majority of definitions highlight the distinction between "traditional software" and AI/ML methodologies.
2) Scientists tend to delve into the philosophical nuances of defining "intelligence," which often complicates the clear classification of specific methods as AI.
3) Global organizations and regulators typically strive to formulate definitions that assist practitioners in categorizing specific methods as AI. However, pinpointing the exact boundary between AI and non-AI methods proves challenging. Some regulators opt not to define AI/ML explicitly and instead adopt a regulatory approach tailored to specific, narrowly defined domains.
4) Regarding ML, the definitions put forth by scientists, global organizations, and regulators are generally more aligned compared to those for AI. Nevertheless, these definitions often lack the clarity necessary for unequivocally classifying specific methods as ML.

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