European Journal of Operational Research 306 (2023) 1–16

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Invited Review

Operational research and artificial intelligence methods in banking ☆

Michalis Doumpos[a,*], Constantin Zopounidis[a,b], Dimitrios Gounopoulos[c], Emmanouil Platanakis[c], Wenke Zhang[c]

[a] Financial Engineering Laboratory, School of Production Engineering and Management, Technical University of Crete, University Campus, Chania 73100, Greece
[b] Finance Department, Audencia Business School, 8 route de la Jonelière, Nantes 44312, France
[c] School of Management, Claverton Down, University of Bath, Bath BA2 7AY, UK

ARTICLE INFO

Article history:
Received 12 August 2021
Accepted 16 April 2022
Available online 28 April 2022

Keywords:
Artificial Intelligence
Operational research
Banking

ABSTRACT

Banking is a popular topic for empirical and methodological research that applies operational research (OR) and artificial intelligence (AI) methods. This article provides a comprehensive and structured bibliographic survey of OR- and AI-based research devoted to the banking industry over the last decade. The article reviews the main topics of this research, including bank efficiency, risk assessment, bank performance, mergers and acquisitions, banking regulation, customer-related studies, and fintech in the banking industry. The survey results provide comprehensive insights into the contributions of OR and AI methods to banking. Finally, we propose several research directions for future studies that include emerging topics and methods based on the survey results.

© 2022 The Authors. Published by Elsevier B.V.
This is an open access article under the CC BY-NC-ND license
(http://creativecommons.org/licenses/by-nc-nd/4.0/)

1. Introduction

The assessment of various financial aspects of banks occupies an essential place in the academic literature because of the crucial intermediation role of the banking industry in financial markets (Ioannidis et al., 2010; Tzeremes, 2015; Zopounidis et al., 2015). Along with an increasing need to use more sophisticated methods in banking research, several studies in this area employ operational research (OR) and artificial intelligence (AI) methods. Thus, the existing literature examines some fundamental research questions in banking research using OR and AI techniques, such as addressing the fairness issue in banking performance evaluation (Chen et al., 2020) and increasing the accuracy of the prediction of default risk and bank failure (Boussemart et al., 2019), as well as helping centralized organizations (e.g., headquarters of banks) to incentivize their units (i.e., bank branches) and optimize their performance (Afsharian et al., 2019). A rising trend in the utilization of OR and AI techniques to address banking challenges indicates their increasing importance and relevance for this field (Akkoç, 2012; Manthoulis et al., 2020; Yao et al., 2017).

This article provides a comprehensive analysis of existing banking studies over the past decade, covering various research topics and applications of OR/AI methods and identifying emerging areas for future research. For clarification, we differentiate OR and AI methods based on their definition and refer to the recent literature that makes a sound distinction between OR and AI methods (e.g., Fethi & Pasiouras, 2010; Gu et al., 2020; Gambella et al., 2021). We start with a presentation of the various topics in banking research that employ (a wide variety of) OR and AI techniques. These topics include bank efficiency and performance evaluation, risk management, banking regulation, mergers and acquisitions (M&A), various bank–customer relationship management studies, and fintech in the banking industry. We follow this presentation with an outline of the most popular OR and AI methods in banking research. In terms of OR techniques, methods such as data envelopment analysis (DEA), agent-based modeling (ABM), Monte Carlo (MC) simulation, and fuzzy logic, among others, have been widely used to evaluate bank efficiency and performance. Various AI techniques have been used in the literature to address classification and forecasting problems arising in banking, including supervised and unsupervised learning approaches. We have, however, excluded multi-criteria decision analysis (MCDA) models because their use in banking has been extensively analyzed in recent times by Zopounidis et al. (2015).

To search the literature, we rely on Scopus, using keyword searches including "banks and machine learning", "banks and ar-

☆ We wish to thank the editor and four anonymous reviewers for their helpful and constructive comments on previous versions of the paper.

* Corresponding author.
E-mail address: kostas@dpem.tuc.gr (M. Doumpos).

https://doi.org/10.1016/j.ejor.2022.04.027
0377-2217/© 2022 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/)

tificial intelligence" and "banks and operational research" as well as searches relating to topics and methods, such as "bank and optimization", "bank and stochastic process", "bank and simulation modeling", "bank efficiency", "bank risk management", "banks and neural networks" and "banks and support-vector machines". In addition, we have selected some specific papers from core journals that our Scopus keyword searches may not fully cover. Ultimately, we identify 338 publications that provide the basis for our analysis.

This article contributes to the literature in three respects. First, we complement and extend previous bibliographic surveys in this area by inclusively reviewing the banking literature that applies OR and AI methods over the most recent period (i.e., the last decade), during which the banking sector has faced several challenges and has undergone essential transformations (e.g., emergence from the global crisis of 2007–2008, adoption of new regulatory requirements such as the Basel III accord, various technological innovations, etc.). Secondly,existing literature review articles have focused on specific methodologies and application areas, such as bank efficiency and data envelopment analysis (Fethi & Pasiouras, 2010; Paradi & Zhu, 2013), as well as business intelligence methods (Moro et al., 2015), while other reviews cover financial services in general without focusing on banking (e.g., Zopounidis et al., 2015; Kaffash & Marra, 2017; Zopounidis et al., 2018). In this study, our objective is to provide up-to-date coverage of the recent trends and advances in the literature on the applications and contributions of OR and AI methods in banking management. In comparison to previous studies, we cover in more detail this crucial area, adopting a broader perspective considering various OR and AI methods,[1] while also taking into account a range of different topics that go beyond bank efficiency analysis. Among others, these include risk management, banking regulations, M&A, customer relationship management, and new developments in the area of fintech.Finally, we provide technical outlines of the most prominent OR and AI methods and analyze how often these techniques are applied to various banking topics. In addition, we shed light by applying more advanced methods recently developed from the widely used basic models in banking research. We contribute to the literature by emphasizing the essential role of advanced methods in providing improved results and new insights in banking research, while highlighting the challenges that should be addressed. Based on this general analysis, we suggest future research directions in banking topics, such as efficiency forecasting, risk assessment, and risk-taking incentives, together with directions for future studies about the methods themselves, including increasing the fitness of applied models, integrating OR and AI methods, and the use of more developed AI techniques in banking, both supervised and unsupervised.

We proceed as follows: Section 2 reviews the role of OR and AI techniques in banking research, and Section 3 describes the methodology of our bibliometric analysis. Section 4 is devoted to our central survey of the literature and the analysis by topic of our main findings, while Section 5 presents the analysis of the application of OR and AI methods in this literature. Finally, Section 6 suggests directions for future research, and Section 7 summarizes and concludes our study.

2. The crucial role of OR and AI techniques in banking

This section provides a basic overview of OR and AI techniques, intending to emphasize their increasingly vital role in addressing practical challenges such as decision-making and forecasting, for which banking applications are a prime target. Moreover, we review some previous studies that have offered comprehensive overviews of OR and AI approaches in various topics and demonstrate how they are used in empirical research.

2.1. OR and decision-making

OR methods aim to support decision-making in a wide variety of applications. In the process, decision-making units (i.e., a person or an organization) express their preferences according to the context of the problem and the available alternatives. For example, the decision-making process must be prudent in the banking industry, which attracts keen attention from individuals, firms, governments, and the markets. Thus, to support decision-making, OR research in banking evaluates the performance of banks using comprehensive sets of internal and external variables, such as balance sheet quality and regulation policies, and facilitates the decision-making process at both strategic and operational levels.

In empirical banking research, prior studies have mainly focused on the impact factors of decision-making. Thus, Rajaratnam et al. (2017) evaluate the loan performance and portfolio risks under the Basel II capital requirements and constraints to make optimal decisions on capital regulation; Papadimitri et al. (2021) investigate the regulatory enforcement action on decision-making in the banking industry in the context of political connections; Karlan et al. (2016) find that sending reminders to bank customers positively influences savings amounts, leading to increased technical efficiency.

In decision-making research, the accurate design of research models and their proper application to practical problems is crucial. The capability of OR models to provide concrete financial decision support is enhanced by technical developments such as the widespread use of data science and analytics (Zopounidis et al., 2018). The importance of OR in banking research is attributed to several aspects: first, OR helps to improve bank productivity based on analytical techniques (Wanke et al., 2016; Kevork et al., 2017); second, OR increases the number of alternative decisions available to bank managers and helps to identify the best ones (Staub et al., 2010; Yang et al., 2010); third, OR serves to improve coordination within an organization about the decisions taken by central and subordinate banks around incentives that work for the overall system (Ding et al., 2017; Afsharian et al., 2019).

In terms of the OR techniques used in banking research, Zopounidis and Doumpos (2002) and Zopounidis et al. (2015) provide strong evidence that MCDA plays a vital role in financial decision-making and is widely used across an array of different financial topics, including banking, corporate finance, and auditing. Moreover, multi-criteria decision models make a significant contribution to individual financial decision-making (Spronk et al., 2016) and serve to provide signals to investors and policymakers when evaluating the performance of financial institutions. Given the existing reviews of the applications of MCDA in finance research, in this study, we omit MCDA approaches and focus on other OR techniques applied in the popular banking topics, including bank efficiency, risk management, bank performance evaluation, regulation, merger and acquisitions, customer-related studies, and fintech.

Fethi and Pasiouras (2010) provide a comprehensive review of OR and AI techniques to evaluate bank efficiency and performance. They find that typical methods in this area are based on DEA approaches. Specifically, they summarize the implementation of DEA, covering issues such as assumptions regarding the type of returns to scale, the selection of orientation, the definition of the inputs and outputs, and the incorporation of environmental variables. Moreover, concerning bank performance topics such as bank failure prediction and credit rating, they report that alternative OR methods such as MCDA are popular. They also document various topics involving several factors that influence bank

[1] We omit the details of some well-studied techniques such as MCDA that have been comprehensively documented in existing literature reviews.

efficiency, such as stock returns, bank ownership, corporate events, regulation reforms, and bank branches' behavior. In our research, we contribute to the literature review by summarizing the studies since 2010 with more banking topics (beyond efficiency analysis), adding the application of AI techniques and various future directions about methodological developments and issues for applied research. Similarly, Paradi and Zhu (2013) conduct a survey of studies on bank branch efficiency and performance using DEA and note that methodological improvement is the subject of most DEA-based studies in bank branches, examples being multidimensional performance evaluation, building efficiency standards into the DEA analysis, and multilayer DEA models for data outliers.

2.2. AI and new models

In recent years, OR methodologies have often been combined with AI techniques, including machine learning models (Andriosopoulos et al., 2019). The development of AI techniques has accelerated during the last three decades. Increases in computing power have allowed AI techniques to be applied to a wide range of subjects, such as business, education, finance, and medicine, accelerating analysis by converting data into clear and actionable insights. The involvement of AI techniques enables both practical and academic issues to be addressed more rapidly, including the estimation of optimal policies, the evaluation of consumer choice, and applying causal inference to average treatment effects (Athey & Imbens, 2019). Unlike traditional statistical models, AI techniques allow the development, through training, of a model that returns a robust output given a specific input. More specifically, AI need not rely on predefined algorithms, such as the functions required in traditional models, but instead finds patterns in data based on previous input/output examples, generating an algorithm accordingly. Perhaps even more significantly, AI can handle complex relationships in data involving images, videos, or text in non-standardized formats.

Machine learning is an essential branch of AI and has become increasingly popular during the last decade. Machine learning approaches address supervised and unsupervised learning tasks. The former focuses on the development of regression and classification models, typically in a predictive context, whereas the latter follows a descriptive approach (e.g., clustering). Moreover, Fethi and Pasiouras (2010) outline the role of machine learning methods in evaluating bank performance, bank failure prediction, and credit rating. They review a small group of studies that use typical machine learning methods. In contrast, our research covers up-to-date advances in AI approaches and technologies, as well as their applications in a much broader range of areas in banking.

Machine learning techniques are favored for their automation potential in increasingly data-rich business environments. Moreover, machine learning approaches can handle high-dimensional raw data and continuously improve their accuracy and efficiency as the number of observations in the data sets available increases (Jordan & Mitchell, 2015).

3. Methodologies

In their comprehensive literature review, Fethi and Pasiouras (2010) focus on the role of OR and AI techniques in the assessment of bank efficiency and performance, covering the period between 1998 and early 2009. Other small-scale surveys and literature reviews can be found in Paradi and Zhu (2013), Moro et al. (2015), Kaffash and Marra (2017), and Gambella et al. (2021). In this paper, we cover the most recent decade, the period from 2010 to 2020, and review the increasingly important role of OR and AI methods in banking research.

Table 1
Publications by type and year.

Year	Articles	Proceedings	Book chapters	Total
2010	25	0	1	26
2011	15	0	0	15
2012	21	1	0	22
2013	17	2	0	19
2014	23	0	0	23
2015	20	2	0	22
2016	23	2	0	25
2017	31	2	0	33
2018	32	3	0	35
2019	40	6	0	46
2020	60	10	2	72

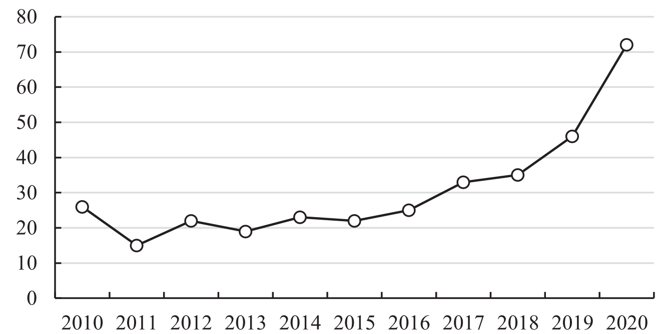

Fig. 1. Numbers of publications per year.

We followed a two-stage process for the identification of the relevant literature. In the first stage, the primary source is Scopus, which is the most comprehensive bibliographic database. More specifically, we searched research studies via different keywords, including both general and specific ones. The keyword framework we used involved "bank", "operational research", and "artificial intelligence". Thus, the primary search keywords were "banks and machine learning", "banks and artificial intelligence", and "banks and operational research." Then, we added more detailed search terms about topics and methods, such as "bank and optimization", "bank and stochastic process", "bank and simulation modeling", "banking industry", "bank efficiency", "bank credit", "bank risk management", "bank failure prediction", "banks and neural networks", "banks and support-vector machines", "banks and random forest" and "banks and DEA". To be more comprehensive, we also manually searched the banking studies in top-rated OR/MS journals using the same keywords. We identified some studies that were not returned when we searched in Scopus with our selected keywords.

In the second stage, we screened the literature to focus on banking-related studies. This unique selection ensured that all the publications related directly to banking research, processing all publications obtained from the first step to identify those not directly related to banking research, including studies on central banks and firm-level lending. After excluding such studies, we identified 338 publications as the basis for our analysis (the complete database is available in the online supplementary appendix); Table 1 shows the number of different publication types by year.

Fig. 1 shows the total number of publications on OR and AI in banking over the last decade. A noticeable increase in recent years, especially for 2019–2020, illustrates the increasing importance of methodological research in the banking industry. Table 2 shows the journals that have published the most articles in our focus areas, the top five accounting for more than 50 percent of these and almost half of our entire sample. It is also worth highlighting that the European Journal of Operational Research and Expert Systems with Applications contribute 65 and 41 publications, respectively,

Table 2
Journals publishing the most articles.

Journal	No. of articles
European Journal of Operational Research	65
Expert Systems with Applications	41
Omega	31
Annals of Operations Research	25
Journal of Banking and Finance	21
Journal of the Operational Research Society	12
Applied Soft Computing Journal	7
Decision Support Systems	7
European Journal of Finance	6
International Journal of Information Technology	6
Operational Research	6
Journal of Economic Interaction and Coordination	5
Journal of Financial Stability	5
International Journal of Forecasting	4
International Transactions in Operational Research	4
Journal of Business Research	4

placing them first and second in the ranking and making them valuable reference sources and potential targets for future papers.

4. Topics for OR and AI methods in banking research

OR and AI methods have been employed in various areas in banking research, including bank efficiency, risk management, bank failure prediction, banking regulation, M&A, and customer relationship management. Bank efficiency accounts for the most significant part, with 108 out of 338 studies concerned with this topic. Moreover, 103 studies apply OR and AI methods to risk management, while 72 focus on bank performance. Customer-related research accounts for 25 publications, and banking regulation and M&A are considered by 10 and 8 studies, respectively. 12 studies are about fintech in the banking industry. In practice, the coverage of different topics is not entirely distinct because some, such as bank efficiency and bank performance, are connected when it comes to comprehensive analysis.

4.1. Bank efficiency

Bank efficiency refers to technical efficiency and allocative efficiency. The former is concerned with producing optimal outputs with minimum inputs and costs, whereas the latter involves the allocation of different inputs to produce a mix of different outputs. Bank efficiency influences economic growth, thus representing an issue of significant interest to society (Tecles & Tabak, 2010). A long strand of studies has documented the importance of bank efficiency assessment. Moreover, the extensive application of OR and AI methods between 2010 and 2020 has helped shift traditional bank efficiency evaluation based on financial ratios to more sophisticated techniques.

Some studies evaluate specific types of efficiency and decompose the overall efficiency to provide a complete picture of the components of productivity change (Yang, 2014; Juo et al., 2016; Fukuyama and Matousek, 2018). Moreover, a strand of literature also investigates the influential factors that have good explanation power regarding efficiency changes over time. It is revealed that some key financial data, such as loans (Barros et al., 2012; Simper et al., 2017), capital (Assaf et al., 2011; Zhou et al., 2019), and liquidity (Fernandes et al., 2018), are typical factors that drive productivity. Additional non-financial factors, such as liberalization (Tecles & Tabak, 2010), bank supervision (Barth et al., 2013), CEO compensation (Matousek & Tzeremes, 2016), operational behavior (Pournader et al., 2017), and ownership structure (Zha et al., 2016; Liu et al., 2020), have also been found to explain bank efficiency and productivity. In the bulk of the literature, bank efficiency is evaluated using various OR methods, among which DEA is the most typical technique (Fethi & Pasiouras, 2010).

Bank efficiency is also one of the impactful factors in bank performance assessment (Feng & Wang, 2018). Efficiency is closely related to operational performance as it enables banks to reach critical goals, such as maximizing productivity and lowering costs (Kourtzidis et al., 2019). Except for efficiency estimation at the bank level, DEA models have also been employed to evaluate the performance of bank branches (Paradi et al., 2011), to predict bank efficiency in combination with AI models (Kwon & Lee, 2015), and to assess the influence of environmental variables such as location and government regulations (Bou-Hamad et al., 2017).

Moreover, a group of research focuses on improving the quality of bank efficiency estimations, using new advanced DEA-based approaches, such as two-stage models, slack-based and network approaches, free disposal hull models, non-convex models, and Bayesian approaches (Holod & Lewis, 2011; Boloori & Pourmahmoud, 2016; Hasannasab et al., 2019; Tavakoli & Mostafaee, 2019; Tsionas, 2020). Moreover, the introduction of machine learning models has also heralded a new dawn for bank efficiency evaluation. Combining DEA with machine learning techniques can offer a robust alternative since DEA can be sensitive to outliers and missing data (Henriques et al., 2020).

4.2. Risk management

Banking risks derive from financial activities, such as loan arrangements, M&A, credit products, and non-financial activities, such as business and strategic reforms, as well as due to new regulations. The main principle of risk management in banking is to establish a solid knowledge of potential risks so that supervisors can manage them under worst-case circumstances and prevent banks from suffering unexpected losses due to risk-taking behaviors.

In financial activities, credit risk is found to have the most significant impact on banking (Doumpos & Zopounidis, 2014), and numerous studies focus on credit scoring, default prediction, and stress testing with AI and OR methods (Akkoç, 2012; Zhang et al., 2014; Lessmann et al., 2015; Butaru et al., 2016; Yao et al., 2017, Kolari et al., 2019). Moreover, OR and AI methods are also applied to other types of risk incurred by the banking system, such as operational risk. For instance, Sanford and Moosa (2012, 2015) used Bayesian networks for operational risk modeling, whereas Mizgier and Wimmer (2018) presented a multi-period model for operational risk measurement based on value-at-risk and expected shortfall. Other studies have focused on specific types of operational risk. For instance, Heidinger and Gatzert (2018) used text mining tools to measure reputation risk. Text mining was also employed byOral et al. (2020) for information extraction from internal documents in a banking institution, and by Saha et al. (2016) for fraud analysis in loan processing. Fraud detection in banking services has also been considered with other advanced AI approaches, such as deep learning (Gómez et al., 2018).

Liquidity risks have also been considered as they are a potentially devasting financial threat to the banking system yet are complicated to measure: risk management research uses tailored OR and AI models to measure the risk trend and identify the most influential factors (Tavana et al., 2018). Another group of studies employs OR and AI techniques in systemic risk management. They study and highlight the interconnectedness in the banking system, which plays a crucial role in the threat of contagions bank failure. Specifically, they focus on issues such as (i) optimizing banking networks to minimize the systemic risk of bank lending (Torri et al., 2018; Sun, 2018; Gupta et al., 2020), (ii) asset allocation (Pichler et al., 2020), (iii) market liquidity (Liu, & Yao, 2016), (iv) policy reforms (Poledna et al., 2014), and (v) the prediction of systemic crises using advanced data analytics approaches relying on recently developed deep learning systems (Lepetyuk et al., 2020; Tölö, 2020).

In terms of managing financial risks, some studies apply OR methods for optimal capital allocation resulting from the evolution of the international regulation (i.e., Basel III). For instance, Lin, Lee, and Kuan (2013) constructed an operational quantification model to monitor and optimize the required capital to control possible losses due to operational risks. Mizgier and Pasia (2016) introduced a multiobjective optimization model to optimize credit capital allocation. Moreover, a group of studies focuses on managing the loan side risks in bank portfolios. Sirignano et al. (2016) proposed the asymptotically optimal portfolio to address the optimization problem for a broad class of dynamic models of loan risk, whereas Chun and Lejeune (2020) considered the risk-based loan pricing problem, considering the marginal risk contribution and the borrower's loan acceptance probability.

4.3. Bank performance

Bank performance reflects how banks allocate various resources to achieve their objectives. In this context, bank failure attracts much attention from the financial markets. In failure, banks can trigger more volatility in the markets than firms because of their essential financial intermediation role. Therefore, the accurate prediction of bank failure is crucial in providing early warning signals to regulators to adjust banking regulations and take precautions, such as increasing capital holdings and being more prudent about credit supply (Gogas et al., 2018; Manthoulis et al., 2020). The widespread use of OR and AI models in banking research illustrates the crucial role of these techniques in accurately forecasting bank failure and classifying banks accordingly.

One group of studies compares traditional models such as logistic regression with machine learning models and finds that the latter perform better by providing more accurate forecasts (e.g., Duman et al., 2012). Besides improving prediction accuracy, machine learning techniques are also applied to find the best variable subset for bank failure prediction. Variable selection is often based on paradigm variables such as "CAMELS" (Capital adequacy, Asset quality, Management capability, Earnings, Liquidity, and Sensitivity to risks), but an increasing number of recent studies have employed machine learning techniques to conduct feature selection to identify the most predictive variables (Carmona et al., 2019; Petropoulos et al., 2020).

Furthermore, OR and AI techniques are also widely used for specific empirical issues, including bank productivity evaluation (Degl'Innocenti et al., 2017; Tsionas & Andrikopoulos, 2020; Afsharian & Bogetoft, 2020), fixed cost allocation (Li et al., 2018; Li et al., 2019; Chu et al., 2020), bank stress testing (Kolari et al., 2019), and bank distress forecasting (Forgione & Migliardo, 2018).

4.4. Banking regulations

Banking regulations are associated with implemented policies, such as the Basel Accords, that can affect bank behavior, and their main objective is to subject banks to specific requirements in terms of their risk management practices. Thus, for example, capital regulations require that banks internalize losses resulting from loan defaults. However, specific regulations, such as safety nets, may encourage banks to take more risks, such as diminishing incentives to assess customers' creditworthiness. OR and AI techniques in banking research can play a crucial role in evaluating the likely and actual impact of regulations on bank performance.

Chortareas et al. (2012) and Barth et al. (2013) focus on capital restrictions and offer insights into their influence on bank efficiency through the application of DEA. Other studies note the influence of financial liberalization on banking; for example, Hermes and Meesters (2015) use OR estimation methods to investigate the effects of financial liberalization policies, such as the lease of supervision power, on bank efficiency. Tziogkidis et al. (2018) use DEA to provide an insight into the effects of financial deregulation under sector reforms based on changes in bank productivity. Poledna et al. (2014) use OR techniques to test credit regulation policies, which have both positive and negative effects on risk management in the banking system.

4.5. Mergers and acquisitions

M&A involve transfers of ownership of financial entities. Mergers refer to the uniting of two existing companies of broadly equal power into a new legal entity, while acquisitions involve the purchasing of one business entity by another. The main objectives of effective M&A are to gain market share, increase profits, and reduce costs, all aiming to increase the benefits to shareholders (Al-Khasawneh, 2013). OR and AI techniques are being implemented to investigate the influence of M&A on banks at different stages of the associated process.

Previous studies mainly applied DEA, and DEA-like methods, to banking M&A. Thus, Amin et al. (2019) focused on target-setting for mergers, supporting decision-makers by identifying the quantities of inputs and outputs required to achieve a given efficiency. Li et al. (2018) decomposed the potential merger gains that measure efficiencies of merger activities to analyze the contribution from different inputs. Moreover, some studies used DEA to evaluate bank performance in the pre-and post-M&A periods: Halkos et al. (2016) evaluated M&A based on bank performance as measured by gains in technical efficiency; Rahman et al. (2016) assessed post-merger bank performance as indicated by market efficiency; and Wu et al. (2011) employed a dynamic DEA approach to evaluate pre-and post-merger businesses in a multiperiod situation.

4.6. Customer-related studies

Banks should have a good knowledge of their customer streams, which directly impact the demand for and supply of financial services. Thus, OR and AI have been applied to customer-related studies in banking, including: (i) customer churn prediction (Farquad et al., 2014), intended to detect the early signs of potential customer loss; (ii) customer satisfaction classification (Grigoroudis et al., 2013), which is helpful for banks in planning and refining their services; (iii) prediction of the openness of potential customers to bank offerings such as financial products (Ładyżyński et al., 2019); (iv) tracking the digitalization of online banking activities, which helps to inform and increase the competitiveness of banking services (Al-Shammari & Mili, 2019); (v) optimizing ATM replenishment and cash management logistics (Lázaro et al., 2018; Ekinci et al., 2019; Chiussi et al., 2020; Salas-Molina, 2020), which is directly related to operational costs and customer demand (excessive cash inventories lead to high holding costs, but inadequate replenishment increases the probability of stock-out and consequent customer dissatisfaction); and (vi) optimizing product portfolios in the interests of both customers and banks themselves (Ali et al., 2017), which seeks to improve bank profitability and customer returns without increasing the overall risk.

4.7. Fintech in the banking industry

The development of fintech introduces new technology into financial services as traditional banking services face challenges, such as providing online lending to maintain and develop market share. Thakor (2020) indicates that P2P platforms and emerging shadow banks take up considerable market segments. Meanwhile, it is noted that the P2P lending has become an alterna-

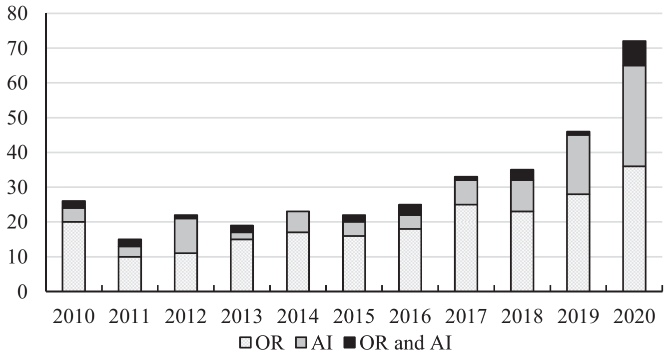

Fig. 2. Development of OR and AI model application in banking research.

tive to bank lending when it comes to serving infra-marginal bank borrowers (Tang, 2019), and 30% of the rapid growth of shadow banks is attributed to fintech, while the rest is explained by the regulation reform (Buchak et al., 2018). The existing studies apply machine learning techniques to optimize bank lending decisions (Metawa et al., 2017; Jagtiani & Lemieux, 2019). In such applications, big data, including non-financial information, could be valuable. For instance, Óskarsdóttir et al. (2019) examined the use of data from mobile phone providers and information derived from social networks to improve the accuracy of credit scoring. In a similar context, non-financial data from an app-based marketplace were also employed by Roa et al. (2021), whereas Kriebel and Stitz (2021) used textual data. Moreover, machine learning methodologies can assist banks by recommending products to target customers according to their historical banking records and preferences. Additionally, some technology-assisted customized financial services, such as cryptocurrencies, smart contracts, Robo-advisor systems, and technologies based on the Internet of Things, also influence banking services in areas such as risk management, financial planning, trading, insurance, etc. (Bunnell et al., 2020; Kou et al., 2021; Pustokhina et al., 2021; Thakor, 2020). Cao et al. (2021) presented a dedicated overview of the literature on various developments in fintech and the related contributions of data science.

5. OR and AI techniques in banking research

The application of OR and AI techniques to the banking industry research has undergone a long development process (Moro et al., 2015; Kwon et al., 2018; Henriques et al., 2020). Fig. 2 depicts the number of studies that have applied OR, AI, or combined techniques to banking research during the 2010–2020 period: it can be seen that both OR and AI methods are widely used and are growing in importance.

Specifically, the growth rate of AI techniques in banking research has been higher than that of OR methods during the period, with sustained increases since 2015. Before 2020, the number of AI-based studies was consistently lower than that of those using OR methods, but, as of 2020, the numbers are almost the same. This significant increase in AI studies indicates that the techniques have attracted more attention from academia specializing in banking industry analysis. The considerable rise in the overall number of studies applying OR and/or AI techniques largely derives from the sharp increase in AI-related studies. The number of studies that combine OR and AI techniques is not as high as those using OR and AI methods in isolation, and this trend has changed little over time.

This study focuses on the OR and AI methods widely applied in banking research, including DEA and its variants, ABM, MC simulation, fuzzy logic, SVMs, NNs, and ensemble methods. In the remainder of this section, we outline the mathematical formulations of these methods, their recent advances, and the banking topics to which they have mainly been applied, as summarized in Table 3. Table 4 shows the frequency with which these techniques have been used in combination.

5.1. OR methods in banking

The application of OR methods in banking research helps to evaluate bank operations and policies, which are essential from the perspectives of government, the market, and individuals. Moreover, studies employing OR methods also assess bank performance and support optimal decision-making in the banking system. In the following subsections, we present the specific OR methods widely used in banking research.

5.1.1. Data envelopment analysis

DEA is popular in the evaluation of the efficiency of banks. In a DEA framework with multiple inputs and outputs, the efficiency score is calculated as the weighted sum of outputs divided by the weighted sum of inputs. The evaluation components of a DEA model, including the decision-making units (DMUs), inputs, and outputs, should be defined in advance. For example, in banking research, efficiency can be evaluated as the proportional changes of the inputs, such as cash balance, fixed assets, and non-performing loans, or the outputs, such as consumer lending, commercial loans, and consumer deposits. In these cases, an increase in inputs does not result in a proportional change in outputs (and a decrease in outputs does not result in a proportional change in inputs). The optimal decision outcomes can be realized by the minimization of inputs and the maximization of outputs.

Conventional DEA models are criticized for assuming an ambiguous (“black box”) production process in which the input variables are transformed to generate output variables without explicitly modeling the transformation (Chen et al., 2010). However, the internal two-stage DEA (see model (1)), first applied in banking research by Seiford and Zhu (1999), can elucidate a separate, transparent process by using the first-stage outputs (e.g., the bank efficiency of subgroups) as inputs in the second stage (Wang et al., 2014). The model assumes n DMUs, each having m inputs and D intermediate outputs, which become the inputs in the second stage:

$$
\begin{array}{llll}
\max & \theta_r^1 = \dfrac{\sum_{d=1}^{D} u_d^A y_{dr}}{\sum_{j=1}^{m} v_j x_{jr}} & \max & \theta_r^2 = \dfrac{\sum_{i=1}^{s} w_i y_{ir}}{\sum_{d=1}^{D} u_d^B x_{dr}} \\
\text{s.t.} & \dfrac{\sum_{d=1}^{D} u_d^A y_{dk}}{\sum_{j=1}^{m} v_j x_{jk}} \le 1,\ k = 1,\dots,n & \text{s.t.} & \dfrac{\sum_{i=1}^{s} w_i y_{ik}}{\sum_{d=1}^{D} u_d^B z_{dk}} \le 1, \quad k = 1,\dots,n \\
 & u_d^A, v_j \ge 0 & & u_d^B, w_i \ge 0
\end{array}
\tag{1}
$$

where y_r is the output produced by the DMU r, x_r refers to the input employed by the DMU, u_d^A denotes the weight of the output in stage 1, u_d^B refers to the input weight in stage 2, and v_j is the weight of the input in stage 1. w denotes the weight of the output in stage 2.

An alternative construction of the two-stage DEA process, which also addresses the ambiguous calculation process of conventional DEA, is to integrate DEA with other methods, including bootstrapping, ordinary least squares (OLS), and NNs, referred to as *external* two-stage DEA. More specifically, external two-stage DEA elucidates the efficiency process over two stages (i.e., see the progression from θ_r^1 to θ_r^2 in model (1) such that the results can be explained with theoretical support, i.e., by explicitly demonstrating the transformation of the first-stage outputs (Tsolas et al., 2020). However, there is controversy around the application of two-stage DEA. For example, Eskelinen (2017) highlights the lack of a preliminary variable selection and explains that DEA cannot address

Table 3
Publications by subject area and methodological approach.

Topic	DEA	Fuzzy	ABM	MC	SVMs	NNs	Ensembles	Others	*Total*
Bank efficiency	102	9	0	4	1	4	1	15	*136*
Risk management	10	4	10	6	24	30	21	49	*154*
Bank performance	38	2	2	9	10	13	7	25	*106*
Bank regulation	7	0	1	0	1	1	1	2	*13*
M&A	8	0	0	0	0	0	0	1	*9*
Customer	0	3	1	0	6	8	6	17	*41*
Fintech	0	1	0	0	0	1	1	10	*13*
Total	*165*	*19*	*14*	*19*	*42*	*57*	*37*	*119*	

Table 4
Articles using combinations (Pairs) of methods.

	Fuzzy	ABM	MC	SVMs	NNs	Ensembles	Others
DEA	9	0	4	0	6	1	19
Fuzzy		0	0	1	2	0	5
ABM			0	0	1	0	2
MC				0	2	0	6
SVMs					12	19	22
NNs						14	23
Ensembles							18

the issue that high-dimensional data may contain less relevant information, thus decreasing the accuracy of the obtained efficiency estimates. On the other hand, Henriques et al. (2020) note that it is necessary to assume different inputs and outputs for different banking studies that focus on distinct bank functions. Moreover, they also point out that the choice of the second-stage model is flexible, allowing different studies to use different models according to their research questions, such as using OLS to analyze the estimated linear relationship between dependent and independent variables or using machine learning methods.

The popularity of DEA, and DEA-like, methods in bank efficiency evaluation can be attributed to several factors. First, bank efficiency represents the ability of banks to turn resources into revenue so that efficient banks can make more profits with lower costs, which leads to growth in the real economy. During banking efficiency decomposition, DEA can evaluate the conversion ratio of inputs to outputs in each unit without the ex-ante requirement of specifying a production or cost function and assessing each element's distinct contribution to the total efficiency (Lin et al., 2017). The second reason for the popularity of DEA-based methods is that, in some studies, bank efficiency is the indicator by which bank behaviors (e.g., increases in capital holdings) or the effects of change (e.g., policy reforms) are evaluated. Another strand of banking studies also applies DEA models to construct bank efficiency measures to study other topics, including bank regulation (Barth et al., 2013), bank performance (Eskelinen et al., 2014), and risk assessment (Boussemart et al., 2019). Finally, improving the accuracy of efficiency measurement is an ongoing challenge in the banking sector. The evaluation of bank efficiency should be robust and consistent as well as prudent when it comes to the development of models to generate accurate efficiency estimates: several methodological studies have modified DEA models using different elements, such as considering slack effects and incorporating fuzzy logic and directional distance models (Asmild & Zhu, 2016; Quaranta et al., 2018; Charles et al., 2019; Kao & Liu, 2019).

The number of DEA applications in banking research has been consistently high. Fethi and Pasiouras (2010) presented a comprehensive overview of the application of DEA-based models to evaluate bank efficiency and reported that banking-related topics ranked number one in studies that used DEA models. Our investigation shows a consistently high number of DEA-based studies in banking since 2010, which may be attributable to the richness of banking data that has become easier to access in the more regulated post-financial crisis period (Liu et al., 2013a). Furthermore, we see variations applied to the conventional DEA model that enhance its application and reinforce its prominent role in banking research.

One significant such development is slacks-based DEA, which dispenses with the notion of proportional change among the inputs and outputs and addresses slacks (or inefficiencies) directly, discarding varying proportions of the original inputs and outputs. *Slacks* are defined as the existence of input excesses and output shortfalls at the optimal efficiency level, and non-zero slacks identify the sources of inefficiency in DMUs, such as non-minimized input for a given output (i.e., an input excess) and non-maximized output with a given input (i.e., an output shortfall). The slacks-based DEA approach depends on two conditions being met: *unit invariance*, meaning that the slacks-based model should be invariant to the units of data, and *monotone*, meaning that the slacks-based model should be monotone in decreasing in each input and output slack of the efficiency evaluation. Thus, in banking research, slacks-based DEA is used to handle the simultaneous non-proportional change of inputs and outputs (Pastor et al., 1999; Tone, 2001), and some studies have proposed an enhanced slacks-based model to measure bank efficiency (Chen et al., 2016; Lozano, 2016).

Like the slacks-based model, the directional distance function is a popular variant to develop conventional DEA. First proposed by Chambers et al. (1998), the directional distance function is a multi-input and multi-output production function that accounts for input contraction (minimization) and output expansion (maximization) simultaneously. The function also reveals the dual correspondence between the directional (technology) distance function and the profit function. In banking research, the directional distance function is used to evaluate bank efficiency and performance. Specifically, Tzeremes (2015) proposed an innovative application of the original range directional distance model (RDM), which considers the dynamic effects of performance level in bank efficiency analysis and uses a time-dependent DEA estimator of directional distance, calculated by RDM and offering an explanation of time-varying effects on bank efficiency[2]. Likewise,Fujii et al. (2018) employed a Russell directional distance model to evaluate change in the total factor productivity (TFP) and the contribution of personal inputs and outputs to overall bank efficiency.

Indeed, the Russell measure is a widely used variant of DEA. Proposed by Fare and Lovell (1978), the measure is an attempt to address the technical efficiency established by Farrell (1957) and captures the existence of slacks in some inputs when the inputs are reduced. In other words, the Russell measure allows for non-radial contraction in inputs; it is mainly applied in bank efficiency and bank performance evaluation. Thus, Hsiao et al. (2011) used a weighted (entropy-based) Russell measure to address the slacks-related challenge of the Debreu–Farrell optimal solution in the conventional DEA model, while Barros et al. (2012) used the Russell

[2] The most recent study by Fukuyama et al. (2021) initially proposed the minimum distance model, which determines a more feasible and practical efficient target compared to the traditional non-radial model.

directional distance to evaluate the influence of undesirable outputs such as non-performing loans (NPLs) on bank performance. Juo et al. (2016) applied a modified Russell measure that integrates the directional distance function and the slacks-based measure to decompose profit-oriented inefficiency in a more general way that considers the simultaneous adjustments of inputs and outputs and slack effects.

Other DEA-based hybrid techniques have been used to improve the model performance of conventional DEA. More specifically, Piot-Lepetit and Nzongang (2014) generated a multi-DEA framework in which the DEA model is defined with different inputs and outputs and performs well in identifying the best-performing banks according to the efficiency scores. Further, Wanke et al. (2016) introduced a fuzzy-DEA (FDEA) framework that delivers strong performance when dealing with uncertainty in inputs.

5.1.2. Agent-based models

Agent-based models (ABMs) are computational models in which individuals or agents are represented as unique and autonomous entities that interact with each other and exogenous environments (Railsback & Grimm, 2019). ABMs can illuminate a wide range of subjects, such as regulation, investment, and banking activities, that involve pursuing a specific goal. The three major components of an ABM are agents, the topology, and the environment. Being unique and autonomous implies that agents are usually distinct in their characteristics and act independently. The topology of an ABM indicates the agents' interactions or connectedness, and the accumulative effects of individual agents within the network drive the system's overall behavior. Environmental factors represent exogenous variables incorporated into the model and may deliver external shocks to the entire system, examples being the financial and credit crises.

Thus, ABM is a simulation framework that approximates complex real-world phenomena. The benefits of using ABM in banking research are threefold: capturing emergent phenomena, providing a natural description of a system, and being flexible (Bonabeau, 2002). Specifically, ABM simulates system behavior by observing agents and their interactions to capture emergent system behavior that depends on the relationships among the agents rather than the attributes of individuals. More recently, Santos and Nakane (2020) applied ABM to simulate bank runs triggered by depositors' decision-making regarding simultaneous withdrawal. Because of the interactions among the depositors, those not influenced by the adverse shock optimize their utility functions and anticipate that the banks may eventually be insolvent if they delay withdrawal to a later date.

This capability of ABM to represent emergent behavior drives its two other benefits: natural description and flexibility. The natural description reflects ABM's ability to describe a system from the perspective of the activities of individual agents that are heterogeneous units rather than from the perspective of whole system processes. For this reason, Xing et al. (2020) employed ABM to study the impact of implementing multiple regulations that directly influence the balance sheet concerning the money supply in heterogeneous banking systems. They insist that the heterogeneity among banks should be modeled in this way because the banking system is composed of institutions that present diverse management capabilities under different regulations, such as the reserve and capital requirements in Basel III. The flexibility afforded by ABM can be observed in the way in which more agents can be added to a model (Rzeszutek et al., 2020), and the complexity of a system description can be tuned by simulating the behaviors and interactions among the agents (Calimani et al., 2019).

Many studies investigate contagion risk by using ABM to simulate the banking network and capture its heterogeneity (Georg, 2013; Ladley, 2013; Liu et al., 2020). Moreover, it is noted that the contagion risk among banks drives systemic risk in a market in which a failure in one sector may give rise to an economic downturn (Poledna et al., 2014). Thus, ABM plays an essential role in evaluating the performance of banks subject to external shocks, such as the financial and credit crises, which may trigger failure in the agent network. Further, some studies used a calibrated or developed form of ABM, such as the BH model introduced by Brock and Hommes (1997), and the actor-based model used to describe banks' behaviors and perform a comparison with the results from ABM (Tedeschi et al., 2019; Crafa, 2019).

5.1.3. Monte carlo simulation

Simulation approaches, typically implemented through MC simulation, enable the estimation of the outcomes of uncertain events and improve decision-making under conditions of uncertainty. MC builds a model of possible results by assigning a random value to the variable with a probabilistic nature; MC then repeats the random process to generate the samples used to calculate the likely outcomes.

The problems handled by MC methods are of two types, namely probabilistic and deterministic. This classification depends on whether the problem is directly generated from or related to the behavior and outcomes of a random process. In banking research, probabilistic problems account for the majority. For instance, in evaluating bank efficiency, Behr (2010) used MC to simulate bank behavior based on historical data and the probability distribution of the parameters. Moreover, MC can numerically address deterministic problems by simulating the concomitant probabilistic issues without direct association with random processes.

MC is widely used in methodological banking research studies, mainly in evaluating bank efficiency, performance, and risk management. Tsionas (2020) used an extensive MC model to investigate the finite-sample properties of a Bayesian DEA. Tsionas and Andrikopoulos (2020) apply MC experiments that repeatedly generate parameter sets to prove the better performance of a copula approximation method. Du et al. (2018) employed MC experiments to obtain insights into the relative performance of a proposed new method. In general, the application of MC in the evaluation of bank efficiency helps to provide sound evidence that methodological studies offer accurate results based on their selected models.

The principal benefit of MC is its straightforward implementation in providing qualified experimental sampling in empirical and theoretical research. MC can calculate the mean of a large sample of numbers, which is more accessible than directly capturing the mean from prespecified distribution functions. It also helps achieve the global optimum in decision-making, which plays a vital role in operational research in the banking industry.

The Markov chain branch of Monte Carlo (MCMC; Metropolis et al., 1953) is a more advanced method in handling a high-dimensional probability distribution. Markov chains involve the idea that a random sample is generated by a sequential process in which each new sample depends on the previous one (Cabello, 2017). In banking studies, MCMC is usually applied to estimate the posterior distribution in Bayesian inference, which helps to generate highly efficient results from large samples. More specifically, Michaelides et al. (2015) used MCMC to estimate the functional form of the cost function to evaluate the performance of a large panel of banks, while Forgione and Migliardo (2018) employed a Bayesian approach in which MCMC is used to draw a sequence of samples from the posterior distribution to forecast bank distress.

5.1.4. Fuzzy logic

The human way of thinking and reasoning is often vague, and fuzzy logic deals with the imprecision that arises when the boundaries of a set are not sharply defined (Zadeh, 1996). The fuzzy logic principle converts imprecise information into numerical values.

The emergence of fuzzy logic challenges classical set theory, which advocates that one object belongs only to one set. Fuzzy logic notes that one individual can belong to more than one set. The benefits of using fuzzy logic are widely noted in banking research. Fuzzy logic can be applied to quantitative analysis to improve the execution of algorithms, such as NNs and SVMs, because of its advantages in modeling with membership functions. It is noted in some banking studies that fuzzy logic is used to enhance the performance of OR techniques and AI classifiers, such as addressing the "black box" issue (Akkoç, 2012; Puri & Yadav, 2015; Dincer et al., 2019). Moreover, fuzzy algorithms have proven to be relatively robust because they are not very sensitive to changing environments when applied to different types of data and study objects in banking research (Wanke et al., 2016). At the same time, fuzzy logic is easy to implement and needs less computing power, saving time when a model is run with large samples (Pournader et al., 2017; Azevedo & Ferreira, 2019).

In banking studies, including bank efficiency evaluation, risk management, and customer-based studies, fuzzy models are usually combined with other techniques. Specifically, Puri and Yadav (2014) applied fuzzy logic to bank efficiency evaluation to extend conventional DEA to handle the issues in a fuzzy environment that constrains the numerical input variables. Zhang et al. (2014) combined fuzzy logic with SVMs and multi-criteria optimization to develop improved classification models resilient to noise and outliers in the data. Al-Shammari and Mili (2019) integrated fuzzy logic with an analytic hierarchy process (AHP) to evaluate subjective and qualitative criteria in the decision-making process.

5.1.5. Other OR methods

Besides the aforementioned techniques, several other OR methods are employed in banking research. Thus, network models (Bachman, 1969) are a popular OR approach in banking risk management. Network models capture the relationships between objects based on their topological structure, and they are frequently used to analyze systematic risk in financial markets, being employed to demonstrate the risks emerging from interconnections in the banking system (Pichler et al., 2020; Gupta et al., 2020). Some studies have employed Bayesian networks to analyze liquidity and operational risks (Sanford & Moosa, 2012; Tavana et al., 2018), and Bayesian networks have also been used to illustrate the probabilistic relationships between banks (Sanford & Moosa, 2015).

Integer programming (IP) is another OR method applied in risk management and customer-based studies. IP is used to address optimization problems in which some or all of the variables are restricted to integers. Some banking studies employ linear integer programming to deal with ATM services, such as redesigning ATM networks (Denstad et al., 2019). Another group of studies on banking systems uses mixed-integer programming (MIP), allowing nonlinear objective functions and constraints to support optimal decision-making (Larrain et al., 2017; Salas-Molina, 2020).

5.2. AI methods in banking

AI techniques have become increasingly popular because empirical research requires the efficient processing of large data sets. AI techniques outperform traditional statistical models by providing more accurate results with fewer model assumptions (Akkoç, 2012). According to our bibliometric analysis (see Table 3), risk assessment, bank performance evaluation, and customer services are the most popular applications for AI methods in the banking literature, using the methods used for classification and prediction tasks.

5.2.1. Support vector machines

SVMs are a machine learning technique used for supervised and unsupervised learning tasks. The intrinsic mechanism of SVMs aims to find the optimal hyperplane that will separate samples, such as loan applicants, into different classes with the largest margin of separation and the lowest rate of misclassification. Given a training set with binary responses, the hyperplane separates the sample data by maximizing the margin between two groups in a supervised classification setting. However, when the sample cannot be linearly separated, slack (error) variables (Cortes & Vapnik, 1995) are introduced with a constant multiplier that defines the trade-off between the minimization of the error and the maximization of the separating margin. For some complex problems, the data can be mapped onto a high-dimensional feature space through a mapping function that allows for linear classification in the new feature space. In such cases, nonlinear classifiers are developed by using appropriate kernel functions (e.g., polynomial, sigmoid, Gaussian kernels, etc.).

In banking studies, SVMs are generally applied to risk management. The importance of such studies is typically attributed to the very rapid development of financial products and/or the enhanced awareness of lending risk in the banking industry, and SVMs are widely used for classifying credit applicants based on their historical credit records (Zhang et al., 2014).

A bulk of the literature uses conventional SVM models, which are more efficient than statistical models such as logistic regression or linear discriminant analysis (Bellotti et al., 2011; García-Palomares & Manzanilla-Salazar, 2012; Feki et al., 2012; Zhang et al., 2014; Ala'Raj & Abbod, 2016; Gogas et al., 2018; Bani-Hani & Khasawneh, 2019; Wu et al., 2019; Beutel et al., 2019; Chen, 2020; Petropoulos et al., 2020). The advantage of SVMs is their high efficiency for both linear and nonlinear classification tasks (Loterman et al., 2012). However, SVMs are sensitive to data quality, and real-world data in banking are typically characterized by noise and outliers.

Thus, some studies improve the accuracy of SVM classification through the introduction of hybrid systems that combine SVMs with other approaches, such as naïve Bayes trees (Farquad et al., 2014), particle swarm optimization (Shie et al., 2012), and ensembles (Wang & Ma, 2012), to reduce the harmful effects of noise and outliers in the sample data.

Moreover, several studies have employed improved SVM approaches and formulations. For instance, Yao et al. (2017) applied least-squares SVM (LS-SVM) as a classification method in a two-stage modeling framework that requires classification and regression to predict loss given default for credit cards. In contrast to standard SVM approaches, which rely on quadratic programming solvers, LS-SVM only requires the solution of a linear system of equations, and is thus computationally less demanding. Maldonado et al. (2017) employed double-regularized SVM formulations, extending standard SVM approaches that rely on a single regularization term (e.g., l_1 and l_2 norms).

5.2.2. Neural networks

Artificial NNs (ANNs), or just "neural networks" (NNs), are computational models that resemble the operation of the human brain, learning from inputs in order to provide an output. An NN is composed of several layers. In a standard feedforward architecture, the first and last layers correspond to the input and output, whereas the intermediate (hidden) layers include multiple neurons, each acting as a processing unit.

Several other NN architectures are tailored for more complicated tasks. For example, convolutional neural networks (CNNs; LeCun, 1989) are a class of deep-learning architectures that have been applied successfully to data with grid-like topologies, such as speech records gathered by banks, through the automation of filter learning/development. In a CNN, a neuron is the product of multiple convolution processes before the final outputs are generated. Recurrent neural networks (RNNs) break the usual NN limitation of moving in the forward direction and progress in a temporally driven sequence. Self-organizing maps (SOMs; Kohonen, 1990) are unsupervised machine learning techniques that reduce the data dimensions by clustering similar patterns into a single group.

In banking studies, numerous studies have used conventional NN models, such as feed-forward NNs, probabilistic NNs, general regression NNs, and wavelet NNs (Tsolas et al., 2020; Abdou et al., 2019; Kwon et al., 2018; Kwon & Lee, 2015; Venkatesh et al., 2014; Saberi et al., 2013; Azadeh et al., 2012). Akkoç (2012) introduced the adaptive neuro-fuzzy inference system (ANFIS), which is the combination of NN and fuzzy logic, for addressing the "black-box" problem in NNs. Oreski et al. (2012) and Oreski and Oreski (2014) proposed new hybrid models that combine a NN with a genetic algorithm (GA) for feature selection. Hybrid NN systems have also been used in other studies, such as by López Iturriaga and Sanz (2015), combining a multilayer perceptron and an SOM to display the classification results visually. Tavana et al. (2018) combined an NN with a Bayesian network, whereas Dželihodžić et al. (2018) integrated bagging and NNs.

In terms of innovation, some studies contribute to the literature by developing NNs based on different data types. For instance, Rönnqvist and Sarlin (2017) adjusted a conventional NN to predict bank distress based on text inputs that compose the semantic vectors in the hidden layers. Text inputs were also used by Kriebel and Stitz (2021) in a deep learning NN model to predict defaults in P2P lending, whereas Ładyżyński et al. (2019) used a deep learning system to analyze transactional data for customer relationship management in retail banking, although they found that an ensemble approach based on the random forest algorithm yields better performance. Similar results were also reported by Gunnarsson et al. (2021), who concluded that deep learning NNs do not outperform shallow NNs and ensemble algorithms in credit scoring applications. However, deep learning approaches have been successfully applied in complex tasks in banking risk management, such as the analysis of counterparty risk (Albanese et al., 2021) and the pricing of complex contracts (Guéant et al., 2020). While such studies rely on a supervised approach, other schemes have also been considered. For instance, Yan et al. (2020) proposed an advanced NN model called the supervised Kohonen network, optimized by a metaheuristic algorithm. They transformed the SOMs into a supervised learning network by adding an output layer after the competition layer.

Enhanced NNs have been applied to bank performance and customer services of the banking topics. For instance, López Iturriaga and Sanz (2015) used a hybrid NN to predict the bankruptcy of U.S. banks given the features of the 2008 financial crisis in terms of bank performance, asset structure, loan portfolio, concentration, and capital. Iturriaga and Sanz found that their modified NN outperformed an SVM model over a short-term prediction horizon, but the SVM performed better for medium- and long-term horizons. NNs are also applied to customer relationship management in banking. For instance, Venkatesh et al. (2014) used NNs to forecast ATM cash demand, based mainly on environmental factors.

5.2.3. Ensemble methods

Ensemble methods use multiple learning models to generate more robust predictions than individual models (Breiman, 2001). Ensemble methods most commonly rely on tree-based models, although other options are possible (Abellán & Castellano, 2017).

Ensemble methods improve the performance of individual prediction models by reducing their variance and/or bias. For instance, bagging (Breiman, 1996), one of the first and simplest ensembles, reduces variance by taking a random subset of the data to create a learning tree for classification purposes. In a further development, Breiman's (2001) random forest (RF) method improves the performance of a decision tree by first using bagging and then artificially restricting the set of features considered for each recursive split. RF is less prone to overfitting and generally performs better than standalone decision trees. Boosting (Schapire, 1990) is another widely applied ensemble scheme, which reduces bias by training a sequence of weak models to compensate for the weakness of their predecessors.

Ensemble methods based on tree models have been applied in several banking topics. For instance, Petropoulos et al. (2020) applied RF to bank failure prediction and found that it has superior predictive performance than other popular benchmarks. Durand and Le Quang (2021) also used RF to analyze the impact of different regulatory variables on the performance of banks and found that RF outperformed other approaches such as Lasso, SVMs, and NNs. In risk assessment, Butaru et al. (2016) applied ensemble tree methods to measure delinquency in the banking system and provide suggestions for more customized supervision based on individual information such as capital ratios. Moreover, in a customer-oriented banking study, Ładyżyński et al. (2019) used tree-based ensemble methods to classify consumers by historical transactional data and predict their willingness to purchase credit.

In addition, ensemble methods that do not depend on tree models have also been applied to banking research. For instance, Finlay (2011) used logistic regression (LR), linear discriminant analysis (LDA), classification and regression trees (CARTs), NNs, and K-nearest neighbor (KNN) as base methods to construct static parallel multiple classifier systems, as well as a multistage classifier system, to increase the accuracy of credit scoring. Erdogan et al. (2019) utilized an SVM as the base classifier in the construction of an ensemble method to assess bank bankruptcy.

6. Directions for future research

In this section, we consider directions for future research on the basis of our comprehensive analysis of the application of OR and AI techniques in the banking literature. We identify several research directions that future studies could explore to develop banking theory and industry practice using these techniques. It is recognized that models provide tools with which to verify theories. Thus, the development of OR and AI techniques should go hand in hand with the improvement of banking theories. In light of this, we present some potential research directions for both topics and methodologies in the following subsections.

6.1. Topic considerations

To evaluate financial stability, the forecasting of efficiency could be explored further. In terms of efficiency estimation, OR methods such as DEA play the most active role in banking research. Better forecasting of efficiency, based on historical records of banking behavior, such as loan performance, capital adequacy, asset quality, and liquidity risks, could positively impact bank risk management because policymakers would provide earlier signals of inefficiency. However, studies of efficiency prediction concerning banking behavior measures are limited compared to those concerned with failure prediction. Thus, future studies could use OR and AI methods to improve efficiency forecasting. Furthermore, as a fundamental direction for AI techniques, unsupervised machine learning models, such as principal component analysis (PCA) and clustering algorithms, could also improve forecasting efficiency.

Despite the considerable number of OR- and AI-based studies in banking risk management, research on non-financial risks has been limited. To be more specific, prior works have developed OR and AI models to evaluate financial risks such as credit, liquidity, and market risk, yet the investigation of conduct risk is limited. Conduct costs are incurred from bank-related objects, financial (in)stability, and reputation. Between 2008 and 2018, the cumulative conduct costs for 20 leading international banks were over GBP 377 billion.[3] Misconduct cases are costly to bank investors, with the fines imposed on offending banks often outweighed by reputational loss (Nguyen et al., 2016). Studies of bank misconduct have focused on financial penalties (Köster & Pelster, 2017) and prevention by board-based monitoring (Nguyen et al., 2016). In conjunction with the development of fintech in the banking industry, conduct risk is also related to cybersecurity in online lending (Bertsch et al., 2020), and similar challenges and opportunities will continue to accompany the ongoing transformation and upgrading of banking services.

Following the 2008 global financial crisis, studies on banking regulation have become increasingly crucial in banking research (Calabrese et al., 2017). Bank supervisors now pay more attention to regulating banks' risk-taking behaviors, for example, by assessing capital structures (Demirguc-kunt et al., 2013; Anginer et al., 2018; Bahaj & Malherbe, 2020). However, studies that use OR and AI methods to investigate bank risk-taking incentives remain limited. Specifically, researchers might evaluate managers' risk-taking behaviors using advanced analytic techniques such as machine learning. Further research could apply such methods to explore the impact of government regulation and managerial behavior on banks. For instance, high- and low-ability managers can have different attitudes and strategies in relation to risk, with the former often being more receptive to risk-taking, while the latter refraining from it; moreover, overconfident managers are likely to take more risks in their investments.

With the development of AI technology, the application of fintech in the financial field challenges the traditional intermediary role of banks, while the rise of online lending disrupts the conventional channels of loan financing. Following the policy reform after the financial crisis, bank lending services are experiencing a shock from the advancement of fintech. Banks can actively adjust their business model by developing online services, while at the same time, the importance of the problems arising from the transition is hard to overestimate: (i) New risk management models. Suboptimal risk management models can lead to poor decision-making and huge costs. Given that the growth of fintech promotes the development of banks, the risk management model should include some new risk factors, such as cyber-attacks or fintech disruptions that may change customer preferences. (ii) New measurement of financial performance. The involvement of financial technology increases working efficiency and saves friction costs in the banking industry. Therefore, when evaluating banking performance, the contribution of technology should be included and the role of some conventional indicators, such as the interest rate, should be further reviewed as the intermediary role of banks is changing. (iii) Information asymmetry. Whether the involvement of technology helps with information disclosure is controversial. Big data decreases the opacity between the banks and their customers, narrows the information asymmetry, and increases market stability. However, using highly efficient techniques to evaluate customers, such as applying sophisticated machine learning techniques to credit scoring, may lead to new biases among different groups (Fuster et al., 2019), causing potential risks in information hiding. (iv) Role of regulations. With the development of fintech around the world, the World Bank Group has assembled its Global Database of Fintech Regulations, which includes country treatments of both foundational regulations, such as anti-money laundering, the countering of financial terrorism and the existence of rules to combat cybercrime, as well as regulations specific to fintech business models, such as digital banking and crypto assets and marketplace lending. The comprehensive regulation resources can promote the exploration of the role of fintech in banking.

Environmental, social and governance (ESG) issues and associated opportunities and risks are becoming increasingly relevant to the banking industry. Beyond traditional financial attributes, it is now widely accepted that ESG plays an important role in evaluating corporate financial performance (Friede et al., 2015). In the banking industry, ESG activities could magnify the differences between financial institutions (Azmi et al., 2021). Therefore, challenges arise for incorporating ESG in studies on the evaluation of bank performance and operations. Meanwhile, growing demand from investors for sustainable products and increasing pressure from regulatory bodies indicate that banks should also consider risks stemming from ESG in their risk management. This also requires the accurate measurement of ESG activities (e.g., ESG ratings) and having a detailed and profound understanding of the strategic role of banks in ESG investment.

6.2. Methodology considerations

The early OR review literature (Ackoff, 1979) points out that research should consider the development of the technology when applying OR methods. OR has undergone successful development during recent decades, with more advanced algorithms, more disciplines embraced, and broader applications. More recently, AI techniques have started to thrive in banking research. Nevertheless, future studies could contribute to the technical development of both OR and AI methods.

Future studies could consider the fitness of the models used. The "robustness concern", which emphasizes model fitness, should always be considered when OR and AI methods are applied to banking research (Roy, 2010). Robustness issues are of crucial importance for decision-making in the banking sector due to the deep uncertainties that affect the decision environment. Methodologies such as stochastic and robust optimization (Bakker et al., 2020) are particularly well-suited in this context, and they have been extensively used in various areas of financial decision-making, including banking (Mulvey & Erkan, 2006; Mukuddem-Petersen and Petersen, 2008; Gülpinara & Pachamanova, 2013; Chehrazi et al., 2019). As the banking sector evolves, new regulatory requirements are imposed, and different risks emerge (e.g., climate risk, the COVID-19 pandemic, etc.; Battiston et al., 2017; 2021; Rizwan et al., 2020), while new challenges arise in enhancing and improving existing modeling formulations and optimization approaches.

Besides optimization models, the handling of uncertainty and issues related to robustness is also relevant for other popular methodologies widely used in banking. For instance, robustness issues in efficiency estimation have attracted considerable interest, and several approaches have been proposed to obtain robust results from models like DEA (Kuntz & Scholtes, 2000; Cazals et al., 2002; Daraio & Simar, 2014). Similarly, robustness is a crucial point for machine learning algorithms as data imperfections and population drift significantly impact the resulting models and the obtained predictions (Goodfellow et al., 2018). Such issues are highly relevant in financial applications, including banking (see, for instance, Hand & Adams, 2014; Sousa et al., 2016). For instance, in deep learning such as LSTM, the overfitting problem resulting from

[3] The project was conducted by the Center for Banking Research (CBR) of Cass Business School. The banks included were Bank of America Corporation, Barclays, BNP Paribas, Commerzbank AG, Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs Group, HSBC, ING Group, JP Morgan & Chase, Lloyds Banking Group, Morgan Stanley, National Australia Bank Group, The Royal Bank of Scotland, Santander, Société Générale, Standard Chartered, UBS and Wells Fargo & Company.

the small sample size can be addressed by regularization, data augmentation, early stopping, and increasing the group in cross-validation, which improves the robustness of the model.

Except for the robustness concern, the financial materiality of OR/AI models and their results is crucial for their adoption in practice. This issue is related to the practical relevance of the models, their interpretability, and the assessment of their results in financial terms. For instance, using machine learning techniques in risk management increases credit rating accuracy. However, it can automatically discriminate against customers from particularly vulnerable groups and fails to sufficiently explain credit denial, which breaks financial inclusion. Thus, it is crucial to demonstrate adequate motivation and good reasons for using AI models. As the banking sector is heavily regulated, analytical models should be built following existing regulations and the practices of the industry. Moreover, the models' interpretability, comprehensibility, and transparency are crucial for success. This issue has gained much interest in AI research (Dietvorst, Simmons, & Massey, 2018; Gilpin et al., 2018; Feuerriegel & Gordon, 2019; Kim et al., 2020; Chen et al., 2022), but it is also relevant for OR models, especially when it comes to the transparency of a model's structure and assumptions as well as the biases of the decision-making process (Montibeller & von Winterfeldt, 2015).

Regarding the assessment of the results derived from analytical decision models, it is worth noting that often, especially concerning AI approaches, statistical performance criteria are employed, while only a limited number of studies directly measure financial performance, such as the return on equities for evaluating loan performance (Verbraken et al., 2014; Fitzpatrick & Mues, 2021; Fuster et al., 2021). Improving statistical performance through data processing does not necessarily translate into better financial performance as indicated by assets and liabilities. Notably, financial performance reflects the actual operating conditions for the financial institutions and is thus more meaningful to customers and regulators.

Addressing the issues raised above remains a challenge. To this end, integrated methodologies and hybrid systems that adopt an interdisciplinary approach and combine elements from both OR and AI could be beneficial. On the one hand, AI provides powerful descriptive and predictive modeling tools, while OR adopts a prescriptive perspective. Thus, the combination of the two paradigms can lead to improved approaches for decision support in banking management. For instance, Bertsimas and Dunn (2017) presented a mixed-integer optimization approach for developing optimal and interpretable classification trees, whereas Carrizosa et al. (2020, 2022) used similar approaches for unsupervised learning (factor and cluster analysis), and Tsolas et al. (2020) considered a combination of NNs with DEA for the evaluation of the performance of bank branches.

Besides the issues raised above, it is worth highlighting some advanced machine learning methods that are barely mentioned and can be explored in future banking research. In terms of efficient methods, a strand of studies identifies that the second-generation gradient boosting machines (GBM) implementations such as XGBoost and LightGBM perform substantially better than ensemble methods such as RFs and the first-generation GBM (Chen & Guestrin, 2016; Ke et al., 2017; Carmona et al., 2019; Gunnarsson et al., 2021). In improving the model interpretation, the SHapley Additive exPlanations (SHAP) value is a recent advancement developed from cooperative game theory and measures the feature importance (Lundberg & Lee, 2017; Lundberg et al., 2020). In banking research, the SHAP value can play an essential role in evaluating the contribution of input indicators to the final predicted outcomes and each prediction, such as results from the decision tree in the ensemble method. Moreover, in the language models, the Transformers that supplant the LSTM can be applied to deal with the soft information in banking operations and research (Vaswani et al., 2017).

Additionally, future studies can also explore the role of *unsupervised AI* methods in banking research. Such methods do not need manual input from human beings. A typical unsupervised machine learning method, the KNN method, enables machines to self-learn the data and undertake classification without labels, which are easily added afterward. Thus, it does not require preliminary manual labeling work, which is time-consuming and subjective.

7. Conclusion

This article presented an extensive review of the crucial role played by OR and AI methods in banking research by analyzing a total of 338 studies published between 2010 and 2020. We described six general topics that employ OR and AI methods to address various crucial banking issues: banking efficiency, risk management, bank performance, banking regulation, M&A, customer-based studies, and fintech in the banking industry. We also outlined the most widely used OR methods, including DEA, ABM, MC, fuzzy logic, and AI techniques, including SVMs, NNs, and ensemble methods. This article contributes to the literature by complementing the prior bibliographic surveys, covering various general banking topics, and summarizing the different methods applied.

We also suggested potential future research directions from both topic and methodology perspectives. Researchers could explore and verify various OR and AI methods in banking studies from a methodological perspective. Thus, regarding future research topics, efficiency forecasting related to the evaluation of financial stability could justify further exploration, as could the investigation of non-financial risks, such as conducting risks, which has received very limited attention in the academic literature to date. Future studies might also explore the impacts of government regulations and managerial behaviors on risk-taking by banks. Finally, future research could also apply other AI methods (e.g., unsupervised machine learning) or fresh combinations of OR and AI techniques to banking research.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2022.04.027.

References

Abellán, J., & Castellano, J. G. (2017). A comparative study on base classifiers in ensemble methods for credit scoring. *Expert Systems with Applications, 73*, 1–10.
Abdou, H. A., Mitra, S., Fry, J., & Elamer, A. A. (2019). Would two-stage scoring models alleviate bank exposure to bad debt? *Expert Systems with Applications, 128*, 1–13.
Ackoff, R. L. (1979). The future of operational research is past. *Journal of the Operational Research Society, 30*(2), 93–104.
Afsharian, M., & Bogetoft, P. (2020). Identifying production units with outstanding performance. *European Journal of Operational Research, 287*(3), 1191–1194.
Afsharian, M., Ahn, H., & Thanassoulis, E. (2019). A frontier-based system of incentives for units in organisations with varying degrees of decentralisation. *European Journal of Operational Research, 275*(1), 224–237.
Ali, Ö. G., Akçay, Y., Sayman, S., Yılmaz, E., & Özçelik, M. H. (2017). Cross-selling investment products with a win-win perspective in portfolio optimization. *Operations Research, 65*(1), 55–74.
Akkoç, S. (2012). An empirical comparison of conventional techniques, neural networks and the three-stage hybrid Adaptive Neuro Fuzzy Inference System (ANFIS) model for credit scoring analysis: The case of Turkish credit card data. *European Journal of Operational Research, 222*(1), 168–178.
Al-Khasawneh, J. A. (2013). Pairwise X-efficiency combinations of merging banks: Analysis of the fifth merger wave. *Review of Quantitative Finance and Accounting, 41*(1), 1–28.
Al-Shammari, M., & Mili, M. (2019). A fuzzy analytic hierarchy process model for customers' bank selection decision in the Kingdom of Bahrain. *Operational Research*, 1–18.
Ala'raj, M., & Abbod, M. F. (2016). Classifiers consensus system approach for credit scoring. *Knowledge-Based Systems, 104*, 89–105.

Albanese, C., Crépey, S., Hoskinson, R., & Saadeddine, B. (2021). XVA analysis from the balance sheet. *Quantitative Finance, 21*(1), 99–123.
Amin, G. R., Al-Muharrami, S., & Toloo, M. (2019). A combined goal programming and inverse DEA method for target setting in mergers. *Expert Systems with Applications, 115*, 412–417.
Andriosopoulos, D., Doumpos, M., Pardalos, P. M., & Zopounidis, C. (2019). Computational approaches and data analytics in financial services: A literature review. *Journal of the Operational Research Society, 70*(10), 1581–1599.
Anginer, D., Demirguc-Kunt, A., Huizinga, H., & Ma, K. (2018). Corporate governance of banks and financial stability. *Journal of Financial Economics, 130*(2), 327–346.
Assaf, A. G., Barros, C. P., & Matousek, R. (2011). Technical efficiency in Saudi banks. *Expert systems with Applications, 38*(5), 5781–5786.
Asmild, M., & Zhu, M. (2016). Controlling for the use of extreme weights in bank efficiency assessments during the financial crisis. *European Journal of Operational Research, 251*(3), 999–1015.
Athey, S., & Imbens, G. W. (2019). Machine learning methods that economists should know about. *Annual Review of Economics, 11*(1), 685–725.
Azadeh, A., Saberi, M., & Jiryaei, Z. (2012). An intelligent decision support system for forecasting and optimization of complex personnel attributes in a large bank. *Expert Systems with Applications, 39*(16), 12358–12370.
Azmi, W., Hassan, M. K., Houston, R., & Karim, M. S. (2021). ESG activities and banking performance: International evidence from emerging economies. *Journal of International Financial Markets, Institutions and Money, 70*, Article 101277.
Azevedo, A. R. S., & Ferreira, F. A. (2019). Analyzing the dynamics behind ethical banking practices using fuzzy cognitive mapping. *Operational Research, 19*(3), 679–700.
Bachman, C. W. (1969). Data structure diagrams. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems, 1*(2), 4–10.
Bahaj, S., & Malherbe, F. (2020). The forced safety effect: How higher capital requirements can increase bank lending. *Journal of Finance, 75*(6), 3013–3053.
Barros, C. P., Managi, S., & Matousek, R. (2012). The technical efficiency of the Japanese banks: Non-radial directional performance measurement with undesirable output. *Omega, 40*(1), 1–8.
Barth, J. R., Lin, C., Ma, Y., Seade, J., & Song, F. M. (2013). Do bank regulation, supervision and monitoring enhance or impede bank efficiency? *Journal of Banking and Finance, 37*(8), 2879–2892.
Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). A climate stress-test of the financial system. *Nature Climate Change, 7*(4), 283–288.
Battiston, S., Dafermos, Y., & Monasterolo, I. (2021). Climate risks and financial stability. *Journal of Financial Stability*, Article 100867.
Bani-Hani, D., & Khasawneh, M. (2019). A recursive general regression neural network (R-GRNN) oracle for classification problems. *Expert Systems with Applications, 135*, 273–286.
Bakker, H., Dunke, F., & Nickel, S. (2020). A structuring review on multi-stage optimization under uncertainty: Aligning concepts from theory and practice. *Omega, 96*, Article 102080.
Behr, A. (2010). Quantile regression for robust bank efficiency score estimation. *European Journal of Operational Research, 200*(2), 568–581.
Bellotti, T., Matousek, R., & Stewart, C. (2011). A note comparing support vector machines and ordered choice models' predictions of international banks' ratings. *Decision Support Systems, 51*(3), 682–687.
Bertsimas, D., & Dunn, J. (2017). Optimal classification trees. *Machine Learning, 106*(7), 1039–1082.
Bertsch, C., Hull, I., Qi, Y., & Zhang, X. (2020). Bank misconduct and online lending. *Journal of Banking & Finance, 116*, Article 105822.
Beutel, J., List, S., & von Schweinitz, G. (2019). Does machine learning help us predict banking crises? *Journal of Financial Stability, 45*, Article 100693.
Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences, 99*(suppl 3), 7280–7287.
Boloori, F., & Pourmahmoud, J. (2016). A modified SBM-NDEA approach for the efficiency measurement in bank branches. *Operational Research, 16*(2), 301–326.
Bou-Hamad, I., Anouze, A. L., & Larocque, D. (2017). An integrated approach of data envelopment analysis and boosted generalized linear mixed models for efficiency assessment. *Annals of Operations Research, 253*(1), 77–95.
Boussemart, J.-P., Leleu, H., Shen, Z., Vardanyan, M., & Zhu, N. (2019). Decomposing banking performance into economic and credit risk efficiencies. *European Journal of Operational Research, 277*(2), 719–726.
Breiman, L. (1996). Bagging predictors. *Machine Learning, 24*(2), 123–140.
Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5–32.
Brock, W. A., & Hommes, C. H. (1997). A rational route to randomness. *Econometrica: Journal of the Econometric Society*, 1059–1095.
Buchak, G., Matvos, G., Piskorski, T., & Seru, A. (2018). Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics, 130*(3), 453–483.
Bunnell, L., Osei-Bryson, K. M., & Yoon, V. Y. (2020). FinPathlight: Framework for an multiagent recommender system designed to increase consumer financial capability. *Decision Support Systems, 134*, Article 113306.
Butaru, F., Chen, Q., Clark, B., Das, S., Lo, A. W., & Siddique, A. (2016). Risk and risk management in the credit card industry. *Journal of Banking and Finance, 72*, 218–239.
Cabello, J. G. (2017). The future of branch cash holdings management is here: New Markov chains. *European Journal of Operational Research, 259*(2), 789–799.
Calabrese, R., Degl'Innocenti, M., & Osmetti, S. A. (2017). The effectiveness of TARP-CPP on the US banking industry: A new copula-based approach. *European Journal of Operational Research, 256*(3), 1029–1037.
Calimani, S., Hałaj, G., & Żochowski, D. (2019). Simulating fire sales in a system of banks and asset managers. *Journal of Banking & Finance*, Article 105707.
Cao, L., Yang, Q., & Yu, P. S. (2021). Data science and AI in FinTech: An overview. *International Journal of Data Science and Analytics, 12*(2), 81–99.
Carmona, P., Climent, F., & Momparler, A. (2019). Predicting failure in the U.S. banking sector: An extreme gradient boosting approach. *International Review of Economics & Finance, 61*, 304–323.
Carrizosa, E., Guerrero, V., Romero Morales, D., & Satorra, A. (2020). Enhancing interpretability in factor analysis by means of mathematical optimization. *Multivariate behavioral research, 55*(5), 748–762.
Carrizosa, E., Kurishchenko, K., Marín, A., & Morales, D. R. (2022). Interpreting clusters via prototype optimization. *Omega, 107*, Article 102543.
Cazals, C., Florens, J. P., & Simar, L. (2002). Nonparametric frontier estimation: A robust approach. *Journal of econometrics, 106*(1), 1–25.
Chambers, R. G., Chung, Y., & Färe, R. (1998). Profit, directional distance functions, and nerlovian efficiency. *Journal of Optimization Theory and Applications, 98*(2), 351–364.
Charles, V., Aparicio, J., & Zhu, J. (2019). The curse of dimensionality of decision-making units: A simple approach to increase the discriminatory power of data envelopment analysis. *European Journal of Operational Research, 279*(3), 929–940.
Chehrazi, N., Glynn, P. W., & Weber, T. A. (2019). Dynamic credit-collections optimization. *Management Science, 65*(6), 2737–2769.
Chen, T., & Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 785–794).
Chen, T. H. (2020). Do you know your customer? Bank risk assessment based on machine learning. *Applied Soft Computing, 86*, Article 105779.
Chen, C., Cook, W. D., Imanirad, R., & Zhu, J. (2020). Balancing fairness and efficiency: Performance evaluation with disadvantaged units in non-homogeneous environments. *European Journal of Operational Research, 287*(3), 1003–1013.
Chen, Y., Cook, W. D., & Zhu, J. (2010). Deriving the DEA frontier for two-stage processes. *European Journal of Operational Research, 202*(1), 138–142.
Chen, Y., Li, Y., Liang, L., Salo, A., & Wu, H. (2016). Frontier projection and efficiency decomposition in two-stage processes with slacks-based measures. *European Journal of Operational Research, 250*(2), 543–554.
Chen, C., Lin, K., Rudin, C., Shaposhnik, Y., Wang, S., & Wang, T. (2022). A holistic approach to interpretability in financial lending: Models, visualizations, and summary-explanations. *Decision Support Systems, 152*, Article 113647.
Chiussi, A., Orlis, C., Roberti, R., & Dullaert, W. (2020). ATM cash replenishment under varying population coverage requirements. *Journal of the Operational Research Society*, 1–19.
Chortareas, G. E., Girardone, C., & Ventouri, A. (2012). Bank supervision, regulation, and efficiency: Evidence from the European Union. *Journal of Financial Stability, 8*(4), 292–302.
Chun, S. Y., & Lejeune, M. A. (2020). Risk-based loan pricing: Portfolio optimization approach with marginal risk contribution. *Management Science, 66*(8), 3735–3753.
Chu, J., Wu, J., Chu, C., & Zhang, T. (2020). DEA-based fixed cost allocation in two-stage systems: Leader-follower and satisfaction degree bargaining game approaches. *Omega, 94*, Article 102054.
Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning, 20*(3), 273–297.
Crafa, S. (2019). From agent-based modeling to actor-based reactive systems in the analysis of financial networks. *Journal of Economic Interaction and Coordination*, 1–25.
Daraio, C., & Simar, L. (2014). Directional distances and their robust versions: Computational and testing issues. *European Journal of Operational Research, 237*(1), 358–369.
Degl'Innocenti, M., Kourtzidis, S. A., Sevic, Z., & Tzeremes, N. G. (2017). Bank productivity growth and convergence in the European Union during the financial crisis. *Journal of Banking & Finance, 75*, 184–199.
Demirguc-kunt, A., Detragiache, E., & Merrouche, O. (2013). Bank capital: Lessons from the financial crisis. *Journal of Money, Credit and Banking, 45*(6), 1147–1164.
Denstad, A., Ulsund, E., Christiansen, M., Hvattum, L. M., & Tirado, G. (2019). Multi-objective optimization for a strategic ATM network redesign problem. *Annals of Operations Research*, 1–27.
Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. *Management Science, 64*(3), 1155–1170.
Dincer, H., Hacioglu, U., Tatoglu, E., & Delen, D. (2019). Developing a hybrid analytics approach to measure the efficiency of deposit banks. *Journal of Business Research, 104*, 131–145.
Ding, J., Dong, W., Liang, L., & Zhu, J. (2017). Goal congruence analysis in multi-division organizations with shared resources based on data envelopment analysis. *European Journal of Operational Research, 263*(3), 961–973.
Doumpos, M., & Zopounidis, C. (2014). *Multicriteria analysis in finance*. New York: Springer.
Du, K., Worthington, A. C., & Zelenyuk, V. (2018). Data envelopment analysis, truncated regression and double-bootstrap for panel data with application to Chinese banking. *European Journal of Operational Research, 265*(2), 748–764.
Duman, E., Ekinci, Y., & Tanrıverdi, A. (2012). Comparing alternative classifiers for database marketing: The case of imbalanced datasets. *Expert Systems with Applications, 39*(1), 48–53.
Durand, P., & Le Quang, G. (2021). Banks to basics! Why banking regulation should focus on equity. *European Journal of Operational Research*.

Dželihodžić, A., Đonko, D., & Kevrić, J. (2018). Improved credit scoring model based on bagging neural network. *International Journal of Information Technology & Decision Making, 17*(06), 1725–1741.

Ekinci, Y., Serban, N., & Duman, E. (2019). Optimal ATM replenishment policies under demand uncertainty. *Operational Research*, 1–31.

Erdogan, B. E., Özöğür-Akyüz, S., & Ataş, P. K. (2019). A novel approach for panel data: An ensemble of weighted functional margin SVM models. *Information Sciences*.

Eskelinen, J. (2017). Comparison of variable selection techniques for data envelopment analysis in a retail bank. *European Journal of Operational Research, 259*(2), 778–788.

Eskelinen, J., Halme, M., & Kallio, M. (2014). Bank branch sales evaluation using extended value efficiency analysis. *European Journal of Operational Research, 232*(3), 654–663.

Fare, R., & Lovell, K. C. (1978). Measuring the technical efficiency of production. *Journal of Economic Theory, 19*(1), 150–162.

Farquad, M. A. H., Ravi, V., & Raju, S. B. (2014). Churn prediction using comprehensible support vector machine: An analytical CRM application. *Applied Soft Computing, 19*, 31–40.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society Series A (General), 120*(3), 253–281.

Feki, A., Ishak, A. B., & Feki, S. (2012). Feature selection using Bayesian and multiclass support vector machines approaches: Application to bank risk prediction. *Expert Systems with Applications, 39*(3), 3087–3099.

Feng, G., & Wang, C. (2018). Why European banks are less profitable than US banks: A decomposition approach. *Journal of Banking & Finance, 90*, 1–16.

Fethi, M. D., & Pasiouras, F. (2010). Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey. *European Journal of Operational Research, 204*(2), 189–198.

Fernandes, F. D. S., Stasinakis, C., & Bardarova, V. (2018). Two-stage DEA-truncated regression: Application in banking efficiency and financial development. *Expert Systems with Applications, 96*, 284–301.

Feuerriegel, S., & Gordon, J. (2019). News-based forecasts of macroeconomic indicators: A semantic path model for interpretable predictions. *European Journal of Operational Research, 272*(1), 162–175.

Finlay, S. (2011). Multiple classifier architectures and their application to credit risk assessment. *European Journal of Operational Research, 210*(2), 368–378.

Fitzpatrick, T., & Mues, C. (2021). How can lenders prosper? Comparing machine learning approaches to identify profitable peer-to-peer loan investments. *European Journal of Operational Research, 294*(2), 711–722.

Forgione, A. F., & Migliardo, C. (2018). Forecasting distress in cooperative banks: The role of asset quality. *International Journal of Forecasting, 34*(4), 678–695.

Friede, G., Busch, T., & Bassen, A. (2015). ESG and financial performance: Aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment, 5*(4), 210–233.

Fujii, H., Managi, S., Matousek, R., & Rughoo, A. (2018). Bank efficiency, productivity, and convergence in EU countries: A weighted Russell directional distance model. *European Journal of Finance, 24*(2), 135–156.

Fukuyama, H., & Matousek, R. (2018). Nerlovian revenue inefficiency in a bank production context: Evidence from Shinkin banks. *European Journal of Operational Research, 271*(1), 317–330.

Fukuyama, H., Matousek, R., & Tzeremes, N. G. (2021). Minimum distance efficiency measure in bank production: A directional slack inefficiency approach. *Journal of the Operational Research Society*, 1–13.

Fuster, A., Plosser, M., Schnabl, P., & Vickery, J. (2019). The role of technology in mortgage lending. *The Review of Financial Studies, 32*(5), 1854–1899.

García-Palomares, U. M., & Manzanilla-Salazar, O. (2012). Novel linear programming approach for building a piecewise nonlinear binary classifier with a priori accuracy. *Decision support systems, 52*(3), 717–728.

Gambella, C., Ghaddar, B., & Naoum-Sawaya, J. (2021). Optimization problems for machine learning: A survey. *European Journal of Operational Research, 290*(3), 807–828.

Georg, C. P. (2013). The effect of the interbank network structure on contagion and common shocks. *Journal of Banking & Finance, 37*(7), 2216–2228.

Gilpin, L. H., Bau, D., Yuan, B. Z., Bajwa, A., Specter, M., & Kagal, L. (2018). Explaining explanations: An overview of interpretability of machine learning. In *Proceedings of the 2018 IEEE 5th international conference on data science and advanced analytics (DSAA)* (pp. 80–89). IEEE.

Gogas, P., Papadimitriou, T., & Agrapetidou, A. (2018). Forecasting bank failures and stress testing: A machine learning approach. *International Journal of Forecasting, 34*(3), 440–455.

Gómez, J. A., Arévalo, J., Paredes, R., & Nin, J. (2018). End-to-end neural network architecture for fraud scoring in card payments. *Pattern Recognition Letters, 105*, 175–181.

Goodfellow, I., McDaniel, P., & Papernot, N. (2018). Making machine learning robust against adversarial inputs. *Communications of the ACM, 61*(7), 56–66.

Grigoroudis, E., Tsitsiridi, E., & Zopounidis, C. (2013). Linking customer satisfaction, employee appraisal, and business performance: An evaluation methodology in the banking sector. *Annals of Operations Research, 205*(1), 5–27.

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. *The Review of Financial Studies, 33*(5), 2223–2273.

Gülpinar, N., & Pachamanova, D. (2013). A robust optimization approach to asset-liability management under time-varying investment opportunities. *Journal of Banking & Finance, 37*(6), 2031–2041.

Gupta, A., Wang, R., & Lu, Y. (2020). Addressing systemic risk using contingent convertible debt – A network analysis. *European Journal of Operational Research, 290*(1), 263–277.

Gunnarsson, B. R., Vanden Broucke, S., Baesens, B., Óskarsdóttir, M., & Lemahieu, W. (2021). Deep learning for credit scoring: Do or don't? *European Journal of Operational Research, 295*(1), 292–305.

Guéant, O., Manziuk, I., & Pu, J. (2020). Accelerated share repurchase and other buyback programs: What neural networks can bring. *Quantitative Finance, 20*(8), 1389–1404.

Hand, D. J., & Adams, N. M. (2014). Selection bias in credit scorecard evaluation. *Journal of the Operational Research Society, 65*(3), 408–415.

Halkos, G. E., Matousek, R., & Tzeremes, N. G. (2016). Pre-evaluating technical efficiency gains from possible mergers and acquisitions: Evidence from Japanese regional banks. *Review of Quantitative Finance and Accounting, 46*(1), 47–77.

Hasannasab, M., Margaritis, D., Roshdi, I., & Rouse, P. (2019). Hyperbolic efficiency measurement: A conic programming approach. *European Journal of Operational Research, 278*(2), 401–409.

Henriques, I. C., Sobreiro, V. A., Kimura, H., & Mariano, E. B. (2020). Two-stage DEA in banks: Terminological controversies and future directions. *Expert Systems with Applications*, 161.

Hermes, N., & Meesters, A. (2015). Financial liberalization, financial regulation and bank efficiency: A multi-country analysis. *Applied Economics, 47*(21), 2154–2172.

Heidinger, D., & Gatzert, N. (2018). Awareness, determinants and value of reputation risk management: Empirical evidence from the banking and insurance industry. *Journal of Banking & Finance, 91*, 106–118.

Holod, D., & Lewis, H. F. (2011). Resolving the deposit dilemma: A new DEA bank efficiency model. *Journal of Banking & Finance, 35*(11), 2801–2810.

Hsiao, B., Chern, C. C., & Chiu, C. R. (2011). Performance evaluation with the entropy--based weighted Russell measure in data envelopment analysis. *Expert Systems with Applications, 38*(8), 9965–9972.

Ioannidis, C., Pasiouras, F., & Zopounidis, C. (2010). Assessing bank soundness with classification techniques. *Omega, 38*(5), 345–357.

Jagtiani, J., & Lemieux, C. (2019). The roles of alternative data and machine learning in fintech lending: evidence from the LendingClub consumer platform. *Financial Management, 48*(4), 1009–1029.

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science, 349*(6245), 255–260.

Juo, J. C., Fu, T. T., Yu, M. M., & Lin, Y. H. (2016). Non-radial profit performance: An application to Taiwanese banks. *Omega, 65*, 111–121.

Kaffash, S., & Marra, M. (2017). Data envelopment analysis in financial services: A citations network analysis of banks, insurance companies and money market funds. *Annals of Operations Research, 253*(1), 307–344.

Kao, C., & Liu, S. T. (2019). Stochastic efficiency measures for production units with correlated data. *European Journal of Operational Research, 273*(1), 278–287.

Karlan, D., McConnell, M., Mullainathan, S., & Zinman, J. (2016). Getting to the top of mind: How reminders increase saving. *Management Science, 62*(12), 3393–3411.

Kevork, I. S., Pange, J., Tzeremes, P., & Tzeremes, N. G. (2017). Estimating Malmquist productivity indexes using probabilistic directional. distances: An application to the European banking sector. *European Journal of Operational Research, 261*(3), 1125–1140.

Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., & Liu, T. Y. (2017). Lightgbm: A highly efficient gradient boosting decision tree. *Advances in Neural Information processing systems*, 30.

Kim, B., Park, J., & Suh, J. (2020). Transparency and accountability in AI decision support: Explaining and visualizing convolutional neural networks for text information. *Decision Support Systems, 134*, Article 113302.

Kohonen, T. (1990). The self-organizing map. *Proceedings of the IEEE, 78*(9), 1464–1480.

Kolari, J. W., López-Iturriaga, F. J., & Sanz, I. P. (2019). Predicting European bank stress tests: Survival of the fittest. *Global Finance Journal, 39*, 44–57.

Kourtzidis, S. A., Matousek, R., & Tzeremes, N. G. (2019). Productivity growth in network models: An application to banking during the financial crisis. *Journal of the Operational Research Society, 70*(1), 111–124.

Kou, G., Akdeniz, Ö. O., Dinçer, H., & Yüksel, S. (2021). Fintech investments in European banks: A hybrid IT2 fuzzy multidimensional decision-making approach. *Financial Innovation, 7*(1), 1–28.

Köster, H., & Pelster, M. (2017). Financial penalties and bank performance. *Journal of Banking and Finance, 79*, 57–73.

Kriebel, J., & Stitz, L. (2021). Credit default prediction from user-generated text in peer-to-peer lending using deep learning. *European Journal of Operational Research*.

Kuntz, L., & Scholtes, S. (2000). Measuring the robustness of empirical efficiency valuations. *Management Science, 46*(6), 807–823.

Kwon, H. B., & Lee, J. (2015). Two-stage production modeling of large U.S. banks: A DEA-neural network approach. *Expert Systems with Applications, 42*(19), 6758–6766.

Kwon, H. B., Lee, J., & White Davis, K. N (2018). Neural network modeling for a two-stage production process with versatile variables: Predictive analysis for above-average performance. *Expert Systems with Applications, 100*, 120–130.

Ladley, D. (2013). Contagion and risk-sharing on the inter-bank market. *Journal of Economic Dynamics and Control, 37*(7), 1384–1400.

Lázaro, J. L., Jiménez, Á. B., & Takeda, A. (2018). Improving cash logistics in bank branches by coupling machine learning and robust optimization. *Expert Systems With Applications, 92*, 236–255.

Ładyżyński, P., Żbikowski, K., & Gawrysiak, P. (2019). Direct marketing campaigns in retail banking with the use of deep learning and random forests. *Expert Systems with Applications, 134*, 28–35.
Larrain, H., Coelho, L. C., & Cataldo, A. (2017). A variable MIP neighborhood descent algorithm for managing inventory and distribution of cash in automated teller machines. *Computers & Operations Research, 85*, 22–31.
LeCun, Y. (1989). Generalization and network design strategies. *Connectionism in Perspective, 19*, 143–155.
Lessmann, S., Seow, H. V., Baesens, B., & Thomas, C. L. (2015). Benchmarking state-of-the-art classification algorithms for credit scoring: A ten-year update. *European Journal of Operational Research, 247*(1), 124–136.
Lepetyuk, V., Maliar, L., & Maliar, S. (2020). When the US catches a cold, Canada sneezes: A lower-bound tale told by deep learning. *Journal of Economic Dynamics and Control, 117*, Article 103926.
Li, F., Zhu, Q., & Chen, Z. (2019). Allocating a fixed cost across the decision making units with two-stage network structures. *Omega, 83*, 139–154.
Li, F., Zhu, Q., & Liang, L. (2018). Allocating a fixed cost based on a DEA-game cross efficiency approach. *Expert Systems with Applications, 96*, 196–207.
Lin, Y. H., Fu, T. T., Chen, C. L., & Juo, J. C. (2017). Non-radial cost Luenberger productivity indicator. *European Journal of Operational Research, 256*(2), 629–639.
Liu, A., Paddrik, M., Yang, S. Y., & Zhang, X. (2020). Interbank contagion: An agent-based model approach to endogenously formed networks. *Journal of Banking & Finance, 112*, Article 105191.
Liu, X., Sun, J., Yang, F., & Wu, J. (2020). How ownership structure affects bank deposits and loan efficiencies: An empirical analysis of Chinese commercial banks. *Annals of Operations Research, 290*(1), 983–1008.
Liu, J. S., Lu, L. Y., Lu, W. M., & Lin, B. J. (2013a). A survey of DEA applications. *Omega, 41*(5), 893–902.
López Iturriaga, F. J., & Sanz, I. P. (2015). Bankruptcy visualization and prediction using neural networks: A study of U.S. commercial banks. *Expert Systems with Applications, 42*(6), 2857–2869.
Loterman, G., Brown, I., Martens, D., Mues, C., & Baesens, B. (2012). Benchmarking regression algorithms for loss given default modelling. *International Journal of Forecasting, 28*(1), 161–170.
Lozano, S. (2016). Slacks-based inefficiency approach for general networks with bad outputs: An application to the banking sector. *Omega, 60*, 73–84.
Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30.
Lundberg, S. M., Erion, G., Chen, H., DeGrave, A., Prutkin, J. M., Nair, B., & Lee, S. I. (2020). From local explanations to global understanding with explainable AI for trees. *Nature Machine Intelligence, 2*(1), 56–67.
Maldonado, S., Bravo, C., López, J., & Pérez, J. (2017). Integrated framework for profit-based feature selection and SVM classification in credit scoring. *Decision Support Systems, 104*, 113–121.
Manthoulis, G., Doumpos, M., Zopounidis, C., & Galariotis, E. (2020). An ordinal classification framework for bank failure prediction: Methodology and empirical evidence for US banks. *European Journal of Operational Research, 282*(2), 786–801.
Matousek, R., & Tzeremes, N. G. (2016). CEO compensation and bank efficiency: An application of conditional nonparametric frontiers. *European Journal of Operational Research, 251*(1), 264–273.
Metropolis, N., Rosenbluth, A. W., Rosenbluth, M. N., Teller, A. H., & Teller, E. (1953). Equation of state calculations by fast computing machines. *The Journal of Chemical Physics, 21*(6), 1087–1092.
Metawa, N., Hassan, M. K., & Elhoseny, M. (2017). Genetic algorithm based model for optimizing bank lending decisions. *Expert Systems with Applications, 80*, 75–82.
Michaelides, P. G., Tsionas, E. G., Vouldis, A. T., & Konstantakis, K. N. (2015). Global approximation to arbitrary cost functions: A Bayesian approach with application to US banking. *European Journal of Operational Research, 241*(1), 148–160.
Mizgier, K. J., & Wimmer, M. (2018). Incorporating single and multiple losses in operational risk: A multi-period perspective. *Journal of the Operational Research Society, 69*(3), 358–371.
Moro, S., Cortez, P., & Rita, P. (2015). Business intelligence in banking: A literature analysis from 2002 to 2013 using text mining and latent Dirichlet allocation. *Expert Systems with Applications, 42*(3), 1314–1323.
Montibeller, G., & von Winterfeldt, D (2015). Cognitive and motivational biases in decision and risk analysis. *Risk analysis, 35*(7), 1230–1251.
Mulvey, J. M., & Erkan, H. G. (2006). Applying CVaR for decentralized risk management of financial companies. *Journal of Banking & Finance, 30*(2), 627–644.
Mukuddem-Petersen, J., & Petersen, M. A. (2008). Optimizing asset and capital adequacy management in banking. *Journal of Optimization Theory and Applications, 137*(1), 205–230.
Nguyen, D. D., Hagendorff, J., & Eshraghi, A. (2016). Can bank boards prevent misconduct? *Review of Finance, 20*(1), 1–36.
Oreski, S., Oreski, D., & Oreski, G. (2012). Hybrid system with genetic algorithm and artificial neural networks and its application to retail credit risk assessment. *Expert Systems with Applications, 39*(16), 12605–12617.
Oreski, S., & Oreski, G. (2014). Genetic algorithm-based heuristic for feature selection in credit risk assessment. *Expert Systems with Applications, 41*(4), 2052–2064.
Oral, B., Emekligil, E., Arslan, S., & Eryiğit, G. (2020). Information extraction from text intensive and visually rich banking documents. *Information Processing & Management, 57*(6), Article 102361.
Papadimitri, P., Pasiouras, F., Pescetto, G., & Wohlschlegel, A. (2021). Does political influence distort banking regulation? Evidence from the US. *Journal of Financial Stability, 53*, Article 100835.
Paradi, J. C., & Zhu, H. (2013). A survey on bank branch efficiency and performance research with data envelopment analysis. *Omega, 41*(1), 61–79.
Paradi, J. C., Rouatt, S., & Zhu, H. (2011). Two-stage evaluation of bank branch efficiency using data envelopment analysis. *Omega, 39*(1), 99–109.
Pastor, J. T., Ruiz, J. L., & Sirvent, I. (1999). An enhanced DEA Russell graph efficiency measure. *European Journal of Operational Research, 115*(3), 596–607.
Petropoulos, A., Siakoulis, V., Stavroulakis, E., & Vlachogiannakis, N. E. (2020). Predicting bank insolvencies using machine learning techniques. *International Journal of Forecasting, 36*(3), 1092–1113.
Pichler, A., Poledna, S., & Thurner, S. (2020). Systemic risk-efficient asset allocations: Minimization of systemic risk as a network optimization problem. *Journal of Financial Stability, 52*, Article 100809.
Piot-Lepetit, I., & Nzongang, J. (2014). Financial sustainability and poverty outreach within a network of village banks in Cameroon: A multi-DEA approach. *European Journal of Operational Research, 234*(1), 319–330.
Poledna, S., Thurner, S., Farmer, J. D., & Geanakoplos, J. (2014). Leverage-induced systemic risk under Basle II and other credit risk policies. *Journal of Banking & Finance, 42*, 199–212.
Pournader, M., Kach, A., Hajiagha, S. H. R., & Emrouznejad, A. (2017). Investigating the impact of behavioral factors on supply network efficiency: Insights from banking's corporate bond networks. *Annals of Operations Research, 254*(1), 277–302.
Puri, J., & Yadav, S. P. (2014). A fuzzy DEA model with undesirable fuzzy outputs and its application to the banking sector in India. *Expert Systems with Applications, 41*(14), 6419–6432.
Puri, J., & Yadav, S. P. (2015). Intuitionistic fuzzy data envelopment analysis: An application to the banking sector in India. *Expert Systems with Applications, 42*(11), 4982–4998.
Pustokhina, I. V., Pustokhin, D. A., Mohanty, S. N., García, P. A. G., & García-Díaz, V. (2021). Artificial intelligence assisted Internet of Things based financial crisis prediction in FinTech environment. *Annals of Operations Research*, 1–21.
Quaranta, A. G., Raffoni, A., & Visani, F. (2018). A multidimensional approach to measuring bank branch efficiency. *European Journal of Operational Research, 266*(2), 746–760.
Óskarsdóttir, M., Bravo, C., Sarraute, C., Vanthienen, J., & Baesens, B. (2019). The value of big data for credit scoring: Enhancing financial inclusion using mobile phone data and social network analytics. *Applied Soft Computing, 74*, 26–39.
Rahman, M., Lambkin, M., & Hussain, D. (2016). Value creation and appropriation following M&A: A data envelopment analysis. *Journal of Business Research, 69*(12), 5628–5635.
Railsback, S. F., & Grimm, V. (2019). *Agent-based and individual-based modeling: A practical introduction*. Princeton University Press.
Rajaratnam, K., Beling, P., & Overstreet, G. (2017). Regulatory capital decisions in the context of consumer loan portfolios. *Journal of the Operational Research Society, 68*(7), 847–858.
Rizwan, M. S., Ahmad, G., & Ashraf, D. (2020). Systemic risk: The impact of COVID-19. *Finance Research Letters, 36*, Article 101682.
Roa, L., Correa-Bahnsen, A., Suarez, G., Cortés-Tejada, F., Luque, M. A., & Bravo, C. (2021). Super-app behavioral patterns in credit risk models: Financial, statistical and regulatory implications. *Expert Systems with Applications, 169*, Article 114486.
Roy, B. (2010). Robustness in operational research and decision aiding: A multi-faceted issue. *European Journal of Operational Research, 200*(3), 629–638.
Rönnqvist, S., & Sarlin, P. (2017). Bank distress in the news: Describing events through deep learning. *Neurocomputing, 264*, 57–70.
Rzeszutek, M., Godin, A., Szyszka, A., & Augier, S. (2020). Managerial overconfidence in initial public offering decisions and its impact on macrodynamics and financial stability: Analysis using an agent-based model. *Journal of Economic Dynamics and Control, 118*, Article 103965.
Saberi, M., Mirtalaie, M. S., Hussain, F. K., Azadeh, A., Hussain, O. K., & Ashjari, B. (2013). A granular computing-based approach to credit scoring modeling. *Neurocomputing, 122*, 100–115.
Saha, P., Bose, I., & Mahanti, A. (2016). A knowledge based scheme for risk assessment in loan processing by banks. *Decision Support Systems, 84*, 78–88.
Salas-Molina, F. (2020). Risk-sensitive control of cash management systems. *Operational Research, 20*(2), 1159–1176.
Santos, T. R. E., & Nakane, M. I. (2020). Dynamic bank runs: An agent-based approach. *Journal of Economic Interaction and Coordination, 16*(3), 675–703.
Sanford, A. D., & Moosa, I. A. (2012). A Bayesian network structure for operational risk modelling in structured finance operations. *Journal of the Operational Research Society, 63*(4), 431–444.
Sanford, A., & Moosa, I. (2015). Operational risk modelling and organizational learning in structured finance operations: A Bayesian network approach. *Journal of the Operational Research Society, 66*(1), 86–115.
Schapire, R. E. (1990). The strength of weak learnability. *Machine Learning, 5*(2), 197–227.
Seiford, L. M., & Zhu, J. (1999). Profitability and Marketability of the Top 55 U.S. Commercial Banks. *Management Science, 45*(9), 1270–1288.
Shie, F. S., Chen, M. Y., & Liu, Y. S. (2012). Prediction of corporate financial distress: An application of the America banking industry. *Neural Computing and Applications, 21*(7), 1687–1696.
Sirignano, J. A., Tsoukalas, G., & Giesecke, K. (2016). Large-scale loan portfolio selection. *Operations Research, 64*(6), 1239–1255.

Simper, R., Hall, M. J., Liu, W., Zelenyuk, V., & Zhou, Z. (2017). How relevant is the choice of risk management control variable to non-parametric bank profit efficiency analysis? The case of South Korean banks. *Annals of Operations Research, 250*(1), 105–127.
Sousa, M. R., Gama, J., & Brandão, E. (2016). Dynamic credit score modeling with short-term and long-term memories: The case of Freddie Mac's database.
Spronk, J., Steuer, R. E., & Zopounidis, C. (2016). Multicriteria decision aid/analysis in finance. *Multiple criteria decision analysis* (pp. 1011–1065). New York, NY: Springer.
Staub, R. B., da Silva e Souza, G., & Tabak, B. M. (2010). Evolution of bank efficiency in Brazil: A DEA approach. *European Journal of Operational Research, 202*(1), 204–213.
Sun, L. H. (2018). Systemic risk and interbank lending. *Journal of Optimization Theory and Applications, 179*(2), 400–424.
Tang, H. (2019). Peer-to-peer lenders versus banks: Substitutes or complements? *The Review of Financial Studies, 32*(5), 1900–1938.
Tavana, M., Abtahi, A. R., Di Caprio, D., & Poortarigh, M. (2018). An artificial neural network and Bayesian network model for liquidity risk assessment in banking. *Neurocomputing, 275*, 2525–2554.
Tavakoli, I. M., & Mostafaee, A. (2019). Free disposal hull efficiency scores of units with network structures. *European Journal of Operational Research, 277*(3), 1027 -10.
Tecles, P. L., & Tabak, B. M. (2010). Determinants of bank efficiency: The case of Brazil. *European Journal of Operational Research, 207*(3), 1587–1598.
Tedeschi, G., Recchioni, M. C., & Berardi, S. (2019). An approach to identifying micro behavior: How banks' strategies influence financial cycles. *Journal of Economic Behavior & Organization, 162*, 329–346.
Thakor, A. V. (2020). Fintech and banking: What do we know? *Journal of Financial Intermediation, 41*, Article 100833.
Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research, 130*(3), 498–509.
Torri, G., Giacometti, R., & Paterlini, S. (2018). Robust and sparse banking network estimation. *European Journal of Operational Research, 270*(1), 51–65.
Tölö, E. (2020). Predicting systemic financial crises with recurrent neural networks. *Journal of Financial Stability, 49*, Article 100746.
Tsionas, M. G. (2020). A coherent approach to Bayesian data envelopment analysis. *European Journal of Operational Research, 281*(2), 439–448.
Tsionas, M. G., & Andrikopoulos, A. (2020). On a high-dimensional model representation method based on copulas. *European Journal of Operational Research, 284*(3), 967–979.
Tsolas, I. E., Charles, V., & Gherman, T. (2020). Supporting better practice benchmarking: A DEA-ANN approach to bank branch performance assessment. *Expert Systems with Applications, 160*(1), Article 113599.
Tzeremes, N. G. (2015). Efficiency dynamics in Indian banking: A conditional directional distance approach. *European Journal of Operational Research, 240*(3), 807–818.
Tziogkidis, P., Matthews, K., & Philippas, D. (2018). The effects of sector reforms on the productivity of Greek banks: A step-by-step analysis of the pre-Euro era. *Annals of Operations Research, 266*(1–2), 531–549.
Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*, 30.
Venkatesh, K., Ravi, V., Prinzie, A., & Van den Poel, D. (2014). Cash demand forecasting in ATMs by clustering and neural networks. *European Journal of Operational Research, 232*(2), 383–392.
Verbraken, T., Bravo, C., Weber, R., & Baesens, B. (2014). Development and application of consumer credit scoring models using profit-based classification measures. *European Journal of Operational Research, 238*(2), 505–513.
Wang, G., & Ma, J. (2012). A hybrid ensemble approach for enterprise credit risk assessment based on support vector machine. *Expert Systems with Applications, 39*(5), 5325–5331.
Wang, K., Huang, W., Wu, J., & Liu, Y. N. (2014). Efficiency measures of the Chinese commercial banking system using an additive two-stage DEA. *Omega, 44*, 5–20.
Wanke, P., Barros, C. P., & Emrouznejad, A. (2016). Assessing productive efficiency of banks using integrated Fuzzy-DEA and bootstrapping: A case of Mozambican banks. *European Journal of Operational Research, 249*(1), 378–389.
Wu, D. D., Zhou, Z., & Birge, J. R. (2011). Estimation of potential gains from mergers in multiple periods: A comparison of stochastic frontier analysis and data envelopment analysis. *Annals of Operations Research, 186*(1), 357–381.
Wu, Y., Xu, Y., & Li, J. (2019). Feature construction for fraudulent credit card cash-out detection. *Decision Support Systems, 127*, Article 113155.
Xing, X., Wang, M., Wang, Y., & Stanley, H. E. (2020). Credit creation under multiple banking regulations: The impact of balance sheet diversity on money supply. *Economic Modelling, 91*, 720–735.
Yan, C., Li, M., & Liu, W. (2020). Prediction of bank telephone marketing results based on improved whale algorithms optimizing S_Kohonen network. *Applied Soft Computing, 92*, Article 106259.
Yang, J. B., Wong, B. Y. H., Xu, D. L., Liu, X. B., & Steuer, R. E. (2010). Integrated bank performance assessment and management planning using hybrid minimax reference point - DEA approach. *European Journal of Operational Research, 207*(3), 1506–1518.
Yang, C. C. (2014). An enhanced DEA model for decomposition of technical efficiency in banking. *Annals of Operations Research, 214*(1), 167–185.
Yao, X., Crook, J., & Andreeva, G. (2017). Enhancing two-stage modelling methodology for loss given default with support vector machines. *European Journal of Operational Research, 263*(2), 679–689.
Zadeh, L. A. (1996). Fuzzy sets. *Fuzzy sets, fuzzy logic, and fuzzy systems: Selected papers by Lotfi A Zadeh* (pp. 394–432).
Zha, Y., Liang, N., Wu, M., & Bian, Y. (2016). Efficiency evaluation of banks in China: A dynamic two-stage slacks-based measure approach. *Omega, 60*, 60–72.
Zhang, Z., Gao, G., & Shi, Y. (2014). Credit risk evaluation using multi-criteria optimization classifier with kernel, fuzzification and penalty factors. *European Journal of Operational Research, 237*(1), 335–348.
Zhou, X., Xu, Z., Chai, J., Yao, L., Wang, S., & Lev, B. (2019). Efficiency evaluation for banking systems under uncertainty: A multi-period three-stage DEA model. *Omega, 85*, 68–82.
Zopounidis, C., & Doumpos, M. (2002). Multi-criteria decision aid in financial decision making: Methodologies and literature review. *Journal of Multi-Criteria Decision Analysis, 11*(4–5), 167–186.
Zopounidis, C., Doumpos, M., & Niklis, D. (2018). Financial decision support: An overview of developments and recent trends. *EURO Journal on Decision Processes, 6*(1), 63–76.
Zopounidis, C., Galariotis, E., Doumpos, M., Sarri, S., & Andriosopoulos, K. (2015). Multiple criteria decision aiding for finance: An updated bibliographic survey. *European Journal of Operational Research, 247*(2), 339–348.