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Applications of Artificial Intelligence in commercial banks – A research agenda for behavioral finance

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ABSTRACT

Artificial intelligence (AI) is receiving increasing attention in business and society. In banking, the first applications of AI were successful; however, AI is mainly applied in investment banking and backend services without customer contact. AI in commercial banking with its focus on customer interaction has received little attention so far. Introducing AI in commercial banking could change business processes and interactions with customers, which could create research opportunities for behavioral finance. Based on this research gap, we conducted a structured literature review to identify applications of AI in commercial banks and the challenges of implementing AI. Our findings suggest that by using AI, commercial banks can reduce losses in lending, increase security in processing payments, automate compliance-related work, and improve customer targeting. Researchers worry about realizing technological advantages; the embedding of AI in business processes; ensuring user acceptance through transparency; privacy; and suitable documentation. Finally, we propose a research agenda for behavioral finance.

1. Introduction

Digitization in combination with advances in data analytics promises huge benefits for corporations in various industries. Corporations have demonstrated how their operations and even their business models benefit from using AI (McKinsey Global Institute, 2018). These AI applications are also promising for the banking sector. In the case of Banco Bilbao Vizcaya Argentaria (BBVA) in Spain, the use of AI has led to increases in revenue and profit as well as a decrease in costs through better customer targeting, the optimization of business operations, and the identification of better locations for the branch networks, among other things (Alfaro et al., 2019). However, AI in banking is currently mainly applied in a limited number of backend services, such as stock prediction and credit rating by huge investment banks or credit scoring by credit card providers, which are traditionally highly computerized (Jadhav et al., 2016).

Contrary to the cases focusing on backend services, those with customer interaction received less attention. Counter to investment and corporate banks, commercial banks focus on customer interaction in terms of lending, processing payments, and collecting deposits (Casu et al., 2016). The limited attention of research on how commercial banks can apply AI in these areas is surprising since several core business areas of commercial banks are already under pressure from new, near-banking competitors. According to McKinsey, several commercial banks' most profitable areas — consumer finance, mortgages, lending to small and medium-sized enterprises (SME), retail payments — could see reductions in revenue between 10% and 40% until 2025 if banks do not react appropriately to increasing competition (McKinsey, 2016). This is a particular problem for commercial banks, whose main business model consists of their lending activities, the processing of payments, and the management of deposits (Casu et al., 2016).

This lack is mirrored by a lack of AI research in the context of commercial banks. There are several literature reviews on AI approaches in banking (Bahrammirzaee, 2010; Jadhav et al., 2016), but none focused on all the core business areas of commercial banks. Based on this gap, we formulate the following research question:

> *How can AI approaches be applied in commercial banking, and what are the benefits compared to traditional information systems (IS)?*

To answer this question, the authors of this paper conduct a structured literature review, following the procedure laid out by Webster and Watson (2002). The literature review is structured around the main business areas of commercial banks and focuses on the benefits and challenges of the application cases of AI in commercial banks. Based on our investigation, we analyze the results from the perspective of behavioral finance and formulate a research agenda.

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The paper is structured as follows: In the upcoming section, the paper's theoretical background is described. In Section 3, a detailed description of the chosen methodology is given. Section 4 describes the results of the structured literature review. In this section, we will analyze the technological changes and the business impact of implementing AI in each core business area of commercial banks. This section also presents a set of challenges of implementing AI approaches in commercial banks that were identified by researchers. In Section 5, we also explore implications for behavioral finance before concluding the paper with Section 6.

2. Background and related work

2.1. Main business areas of commercial banks

Four aspects make commercial banks unique: products/ services they offer; activities they get involved in; the customers that they target; and the implications that the previous three have for customer relationships (Casu et al., 2016). Commercial banks, as described by Casu et al. (2016), are institutions that focus on lending, taking deposits, and processing payments, making them not only the main operators of the payment system but also the main providers of credit to enterprises and households.

All these focus areas of commercial banks could benefit from the use of AI. To ensure that banks can lend profitably, they need to properly assess the creditworthiness of their customers. In the context of processing payments, it is important for banks to ensure that the payment infrastructure, such as automated teller machines (ATMs) for cash payments and computers for processing digital payments, are safe to use, operational, and serviced at appropriate intervals. It is noteworthy that non-cash payments have been on the rise in recent years, giving commercial banks detailed data about their customers' shopping behavior (Harasim, 2016).

Even though commercial banks are focused on lending, deposits, and payment processing, there are two additional areas that commercial banks cannot get around when doing business. First, commercial banks need to ensure compliance with all relevant laws and regulations. Commercial banks need to comply with several banking-specific regulatory frameworks such as the Basel Accords (Bank for International Settlement, 2017) that puts restrictions on commercial bank's lending activities and the Payment Service Directives (European Commission, 2015) that affects all companies offering payment solutions. Legal requirements have a significant impact on the amount of risk that commercial banks can take as well as on operational procedures in commercial banks.

Second, commercial banks also need to market and sell their products and services to customers. What makes customer relationship management (CRM) in commercial banks a challenge is that the products offered by different commercial banks are often fairly homogeneous. This makes effective targeting of customers a determinant factor in commercial banking. One way for commercial banks to do that is through the management of the relationship with their customers.

2.2. IS in commercial banks

In recent decades, banks introduced IS with big benefits for themselves as well as for their customers. Seese et al. (2008) point out that the benefits of IS in commercial banking include improved business processes and services.

For bank customers, a large change made possible by IS is the option to manage accounts via the internet and make and receive internet- and card-based payments (Harasim, 2016; Krueger and Leibold, 2008). These functionalities are enabled by a client–server system in which customer data and account information are stored on a central server and customers can gain access via the internet (Krueger and Leibold, 2008). In lending, several software implementations are available on the commercial market (e.g., SAP's (SAP, 2019a) "Commercial Banking Operations" module). Internally, regulatory technology (RegTech) solutions aid banks in dealing with compliance-related issues (Butler and O'Brien, 2019). CRM technologies help with the interaction between commercial banks and their customers (Jayachandran et al., 2005). Table 1 presents a short definition of the core business areas of commercial banks as well as a description of the most common IS used in the respective business area.

2.3. A new wave of IS

Seese et al. (2008) point out that in earlier years, new IS has had a large impact on the financial industry, particularly in the area of mathematical finance. In recent years, however, more powerful technological innovations have changed the IS landscape. New challenging tasks can be addressed as more data is available and computing power has become more affordable, which boosts AI (Halevy et al., 2009).

In the literature, there is no consistent definition of AI, and the term AI is still a topic of discussion. In a proposal for the Dartmouth conference, one of the earliest conferences focusing on AI, McCarthy et al. (1955) stated that they wanted to research "machines that can be made to simulate [intelligence]". Russel and Norvig (2013) define AI as the study of an intelligent agent that performs actions. Huang et al. (2004) state that what makes AI different from other methods is that AI derives models from the structure of the data, without anyone needing to tell the program what to look for or how to act.

Another challenge is that the term AI has been hyper-advertised in recent years. The term "AI" is frequently used interchangeably with the terms "data mining" and "machine learning", even though the three terms are noninterchangeable. "Machine learning" is defined as a computer's ability "to adapt to new circumstances and to detect and extrapolate patterns" and is a sub-area of AI (Russel and Norvig, 2013). "Data mining" is defined as "the process of exploration and analysis, by automatic or semiautomatic means, of large quantities of data to discover meaningful patterns and rules" (Berry and Linoff, 2000). In data mining, AI is frequently used for the analysis of data and for the extraction of patterns.

One approach to pinning down the meaning behind AI is the contrast to methods used in econometrics. Even though econometric models are a logical solution to many problems, AI is quite different. While econometric methods apply pre-defined statistical models to data, AI takes the data as a starting point, which can lead to superior performance (Butaru et al., 2016). However, AI performance is highly dependent on the data that is used in the training process. Barocas and Selbst (2016) point out that "an algorithm is only as good as the data it works with". Including biased data will therefore lead to biased results. This means that AI could implicitly take over the same biases as prior decision-makers (Barocas and Selbst, 2016).

For the purpose of this paper, Huang et al.'s (2004) definition of AI will be used. In this paper, we intend to review literature on applications of AI in commercial banks.

2.4. Motivations for using AI in commercial banks and challenges of current IS

In recent years, several major trends have put the traditional business model of commercial banks under pressure. First, a rise

Table 1
Core business areas of commercial banks.

Core business area	Description of business area	IT systems used in business area
Lending	A loan is a type of financial claim to the payment of a future sum of money and/or a periodic payment of money (Casu et al., 2016). Commercial banks lend money to their customers in several ways, such as credit cards, consumer loans, and corporate loans.	• IS from external vendors (i.e., SAP (SAP, 2019a) "Commercial Banking Operations" Module)
Taking/managing deposits	Taking deposits is defined as "collecting funds from surplus units", (i.e., companies and households that earn more money than they spend (Casu et al., 2016)).	• Branch and ATM network where customers can deposit cash (Lázaro et al., 2018) • In-house-developed IS (server-based IS, where customers can access their account information and also make payments; (Krueger and Leibold, 2008) • SAP software modules (SAP, 2019b)
Processing payments and providing/managing infrastructure/payment channels	Payment processing is an example of an organized arrangement for transferring value between parties (Casu et al., 2016).	• ATM networks serviced by banks (Zapranis and Alexandridis, 2009) • Server-based IS, where customers can access their account information and make payments (Krueger and Leibold, 2008) • Card and digital payment networks (Harasim, 2016) • SEPA harmonizes the standards used for payments across the Euro area (as well as other EU and non-EU countries) (European Commission, 2018)
Compliance with regulations	"Regulation relates to the setting of specific rules of behavior that firms need to abide by — these may be set through legislation of be stipulated by the relevant regulatory agency" (Casu et al., 2016).	• Compliance and regulation is still an area with a lot of manual labor (Marenzi, 2017) • RegTech systems are increasingly helpful (Butler and O'Brien, 2019)
Marketing and sales	"Essentially, marketing is concerned with the efficient and needs-based design of exchange processes" (Meffert et al., 2018) This includes advertising, CRM.	• CRM technology (Jayachandran et al., 2005) • Salesforce automation technology (Krishnan et al., 2014)

in competition has shown that banks no longer have a monopoly on several of their most profitable business areas (Hu, 2005; McKinsey, 2016). Second, a change in consumer preferences impacts both the perception of the banks' service offering and the options that banks can have for servicing their customers (Jakšič and Marinč, 2015; McKinsey, 2016). Third, the amount of regulations is putting pressure on the current, mostly manual compliance processes in banks (Butler and O'Brien, 2019; Martens et al., 2016). Fourth, changes in the behavior of fraudsters are increasing the need for banks to reinforce their security measures. Fifth, the scale of the existing network of branches and the scale of IT infrastructure is putting pressure on banks, due to becoming harder and more expensive to service (Lázaro et al., 2018; Zapranis and Alexandridis, 2009). The following subsections will go into more detail about the specific challenges as well as AI-based solutions.

2.4.1. Increasing competition

For a long time, commercial banks had their regional niches and protected markets. However, this changed with digitization and the availability of e-services. Hu (2005) concludes that "deregulation within the financial service industries and the widespread acceptance of new technologies is increasing competition in the finance marketplace". Further, more and more non-banking organizations are actively targeting the most profitable parts of banking (McKinsey, 2016). This means that new competitors are offering specialized services that were previously reserved only for banks, such as processing payments (PayPal), exchanging currency (Transferwise), and providing loans (MyBank). Several competitors, such as the Chinese lender MyBank, are employing AI to make their services more efficient, more effective, and cheaper (Reuters, 2018). This increase in competition means that customers have more choice as to where they want to open bank accounts, how they want to make payments, and where they want to take out a loan (Hormozi and Giles, 2004).

However, there is a way for commercial banks to fight back: by using AI in their organization. BBVA, for instance, has used AI to decide on the optimal placement for their branch offices in Spain, to help customers improve their methods for budgeting, and improved customer targeting (Alfaro et al., 2019). AI can also help banks with that change, for instance, by reducing costs and automating mostly manual processes (Butler and O'Brien, 2019; Khandani et al., 2010).

2.4.2. Changing customer preferences

In addition to the rise in competition, the preferences of bank customers have also changed. "Bank customers increasingly wish to be empowered, continuously connected, and entertained" (Jakšič and Marinč, 2015). Due to the increase in competition, the ties between banks and customers is becoming progressively weaker, and consumers are increasingly switching to companies with the most attractive offer (McKinsey, 2016). Specifically, millennials, SMEs, and people without access to the banking system are engaging in cherry-picking (McKinsey, 2016). This means that changing consumer preferences in combination with the increasing competition is putting the banks' business model under pressure.

However, these changes in consumer behavior are not only a challenge for banks but could also be seen as an opportunity. For instance, analyzing the financial behavior of customers by analyzing payments can also help commercial banks in marketing. AI approaches can provide banks with the technological means to extract information about the behavior of their customers, as shown by Martens et al. (2016). Given the customer's willingness to try new things, commercial banks might also have the ability to investigate how the implementation of AI in their core business areas is best accepted. Banks can use experimental methods to investigate the acceptance of AI.

2.4.3. Increasing regulatory demands

As a result of the last financial crisis, banks are also faced with a rise in regulatory demands. This rise is significant, as over 50,000 regulations were published between 2009 and 2012 in G20 countries, and is driving costs for commercial banks (Butler and O'Brien, 2019). In 2015, more than 50,000 regulatory updates were published, representing a 100% increase over 2012, so that monitoring, interpreting, and complying with regulations is a challenge, even for larger banks (Butler and O'Brien, 2019). As a result, the banking industry is now one of the most regulated industries in the world (Hartmann-Wendels et al., 2019). In addition to the amount of regulation, another issue is the fact that compliance is still based on the manual labor of specialized experts (Marenzi, 2017), who can be hard to find and train.

However, there is a technical solution that promises help: RegTech. "RegTech is IT that (a) helps firms manage regulatory requirements and compliance imperatives by identifying the impacts of regulatory provisions on business models, products, and services; functional activities; policies; operational procedures; and controls; (b) enables compliant business systems and data; (c) helps control and manage regulatory, financial and non-financial risks; and (d) performs regulatory compliance reporting" (Butler and O'Brien, 2019). AI approaches are extremely promising in this area since they can decrease the amount of time spent on routine tasks and the amount of human error (Aziz and Dowling, 2019). This means that using AI approaches in compliance could free up significant resources and might even fill a gap that banks could not otherwise fill. Early applications of AI-based RegTech are already receiving public attention as well as support from (British) regulators (Butler and O'Brien, 2019).

2.4.4. Changing behavior of fraudsters

Another important issue is the topic of security. From an IT perspective, there are a handful of preventive measures, such as Secure Sockets Layer (SSL) encryption, that attempt to prevent security breaches and fraud (Krueger and Leibold, 2008). However, SSL encryption does not seem to be able to handle the changing behavior of fraudsters "—" the cost of global payment card fraud grew by 19% [in 2016] to reach $14 billion" (Jadhav et al., 2016). New ways of conducting fraud also require new ways to combat fraud. This means that there is a need for banks to find ways to improve on existing security measures.

AI approaches can pick up on behavioral changes on the side of the fraudsters. Jadhav et al. (2016) point out that AI is already showing great promise in that area. Kumar et al. (2019), for instance, present an AI-based system that detects whether a fraudster has targeted an elderly customer.

2.4.5. The scale of the business network

The scale of current IS and the branch network of banks is also a challenge for banks. For instance, the associated costs for servicing and maintaining an ATM network is a significant cost factor for commercial banks (Zapranis and Alexandridis, 2009). Also, the optimal placing of branches can have a significant impact on the revenue of commercial banks (Alfaro et al., 2019). Optimizing the ATM and branch network of commercial banks can have a significant positive impact on their bottom line.

AI approaches have been shown to help with these problems. For instance, Lázaro et al. (2018) automate the scheduling of the cash delivery and pickup for ATMs and branches. Alfaro et al. (2019) state that BBVA used AI to optimize the locations of their branches and thereby increased revenue. This shows that AI can be used to increase revenue and reduce the cost of operating ATMs and branches of commercial banks.

3. Methodology

This structured literature review is based on the method proposed by Webster and Watson (2002), which consists of three steps and leads to the creation of a concept matrix on which the academic literature can be evaluated:

1. Identifying relevant literature
2. Structuring the review
3. Theoretical development

Table 2
Definition of dimensions.

Dimension	Definition
Technology	Which family of AI algorithms is used in the paper?
Performance	How does the AI approach compare to existing techniques in the business area?
Data source	Who provided the data?
Data type	Which type of data was used — transactional data, social media data, or text?
Expected business impact	Which economic impact does the integration of the proposed method have?
Managerial implications	Which managerial implications does the proposed method have?
Challenge of the proposed approach	Which challenges of the approach did the authors of the paper identify?

3.1. Identifying the relevant literature

As a starting point, the database search focused on A+- and A-rated journals in the Banking and Finance section and A+-rated journals from the IS-section of the VHB-JOURQUAL 3 ranking (VHB, 2015), as well as the proceedings of three relevant conferences and three additional journals that are relevant to the subject. VHB-JOURQUAL 3 ranks a large set of academic journals in several business-related fields, and the ranking is the result of a ballot by 2600 academics in the field (VHB, 2019). The three conferences had a clear focus on IS and had a track that focuses on IS in finance and banking. The additional journals were chosen due to their focus on the application of expert systems and intelligent agents, and their quality was intentionally chosen to be high to focus on the most relevant issues in commercial banks. The query focused on papers published between January 2009 and August 2019 to focus on the most current discussion in the academic literature.

After that, search keywords were defined using the building blocks approach from Rowley and Slack (2004). For the finance-oriented journals, the keywords "artificial intelligence", "machine learning", and "data mining" were used. To exclude papers without a clear link to commercial banking, the search query excluded papers with the terms "option" and "stock prices". The keywords for the finance-oriented journals were intentionally chosen to be less restrictive since the authors wanted to ensure that emerging topics were included in the review. As argued in Section 2.3, the terms "AI", "Machine Learning" and "Data Mining" are used interchangeably in finance literature. The keywords for the computer science-related sources had to be more specific to the context of this review. For this reason, seven keyword combinations – "data mining", "bank", and one of the terms "credit risk", "deposit", "payment processing", "money laundering", "RegTech", "compliance" and "customer relationship management" – were used in the search for publications.

The database query resulted in a set of 337 possibly relevant publications. According to Webster and Watson (2002), the next step is an abstract scan. During the abstract scan, all papers that were unrelated to the research were excluded. Specifically, all publications that covered AI algorithm applications in the context of commercial banks were included. Papers covering AI in areas not covered by commercial banks (i.e., trading and portfolio management); the investigation of systematic risks or macroeconomic issues with the help of AI; game-theoretic analyses; and papers covering variable selection or model optimization methods were excluded. The abstract scan resulted in a set of 34 relevant papers. As recommended by Webster and Watson (2002), a forward–backward scan resulted in ten additional publications. In total, 44 papers were reviewed.

3.2. Structuring the review

The second step of the review was structured in a concept-centric way. In order to do this, a concept matrix as defined by Webster and Watson (2002) was constructed. A concept matrix is a method for ensuring that the review is centered around concepts, not authors (Webster and Watson, 2002), and is constructed by identifying dimensions relevant to the review and how these dimensions are addressed in the academic literature.

3.3. Theoretical development

To extract patterns from the literature, an iterative qualitative content analysis as specified by Patton (2002) was conducted. We repeatedly performed qualitative content analyses until patterns among the papers emerged. This way, the concept matrix was gradually refined. Table 2 contains the dimensions that were used for the development of the concept matrix.

4. Discussion of results

The dimensions described in Table 2 will be integrated into the review as displayed in Fig. 1. First, the paper will look at the individual business areas of commercial banking and investigate how "technology", "data source", "data type", "performance", "expected business impact", and "managerial implications" relate to each of the business areas. Second, we will aggregate and summarize the challenges of using AI in commercial banks that were identified in the academic literature

4.1. Lending using AI

With regard to lending, AI has major impacts from technological and business perspectives. From a technological point of view, the use of AI enables commercial banks (1) to make more accurate predictions with previously unused data types and (2) to use new algorithms in the analysis of customer data. Using AI in lending also has business implications for commercial banks. More accurate credit risk assessments reduce the losses for banks, regardless if commercial banks analyze credit cards or consumer or corporate loans.

4.1.1. What is AI changing in lending?

4.1.1.1. More accurate predictions can be made with previously unused data types. In our review, it became clear that AI increases the number and varieties of data types considered for credit risk assessment. Several papers show that using transaction data has a positive impact on the performance of predictive algorithms in the context of predicting loan default (Tobback and Martens, 2019; Kvamme et al., 2018; Khandani et al., 2010). In their review, Onay and Öztürk (2018) conclude that the inclusion of non-traditional data sources such as utility bills, telecom data, and data from social media sites is a real game-changer for commercial banks. Óskarsdóttir et al. (2018) analyze smartphone-based data, such as calls, texts, and apps, and socio-demographic data to estimate the probability of consumer default and conclude that the resulting model can predict defaults in microlending more precisely. Zhang et al. (2015) combine financial variables with a sentiment score derived from internal due diligence reports to accurately predict whether loan applications of customers of a Chinese lender will be accepted. Butaru et al. (2016) use account-level credit card data in combination with credit bureau data to precisely estimate credit card delinquencies. Sigrist and Hirnschall (2019) use data about online user behavior, such as log-in and click data; ratings for SMEs from social media platforms; and more traditional variables, such as ratios from balance sheets and income statements and company and loan characteristics, to successfully predict default of SMEs in Switzerland. Bücker et al. (2013) point to the fact that models trained only on data from people who were given a loan might be biased; they investigate the effect of including data from rejected applicants and ways to improve the evaluation of credit risk by using this data. Scholars conclude that the use of these data sources and data types contain relevant signals for the estimation of credit risk and have a positive impact on the predictive performance of credit risk models (Bücker et al., 2013; Khandani et al., 2010; Onay and Öztürk, 2018; Sigrist and Hirnschall, 2019; Zhang et al., 2015).

4.1.1.2. A greater variety of algorithms in credit risk estimation. This enhanced capability to make accurate predictions using more diverse data is also based on a variety of new algorithms. Sigrist and Hirnschall (2019), for instance, propose an algorithm that can work with ratings from social media websites and online user behavior data, such as log-ins and click data, in addition to more traditional data about company and loan characteristics and data from credit bureaus to predict SME defaults. Neural networks are used by several authors for the estimation of credit risk (Falavigna, 2012; Óskarsdóttir et al., 2018). In their analysis of smartphone-based data, Óskarsdóttir et al. (2018) also use random forests. Tobback and Martens (2019) use a support vector machine (SVM) to analyze consumer transactions. Khandani et al. (2010) use regression trees to integrate consumer transactions, account balance data, and credit bureau data to predict credit card delinquencies. Chen and Huang (2011) show that artificial neural networks can predict credit default using traditional customer data. Kvamme et al. (2018) use convolutional neural networks to predict mortgage defaults. Wang and Ma (2012) use an ensemble method based on an SVM and the bagging and random subspace method to classify companies into risky and non-risky borrowers. Dereli̇oğlu and Gürgen (2011) use a multilayer perceptron – another form of neural network – to predict the creditworthiness of SMEs in Turkey. In their literature review, Jadhav et al. (2016) find that several AI algorithms can be used for analyzing financial statements in an attempt to check for financial statement fraud. Xiong et al. (2013) analyze credit card data to predict personal bankruptcies. Chrzanowska et al. (2009) use a decision tree and a boosting algorithm to predict which customers will default on their mortgages. Sarlija et al. (2009) analyze behavioral data extracted from credit card statements using neural networks to estimate the default time for credit card customers. Li et al. (2016) propose a hybrid model based on artificial neural networks and the logistic regression for credit scoring. This shows that AI can process previously unused types of data in the context of lending.

In addition to being able to process more types of data, AI is also more accurate than traditional models in consumer credit risk estimation, such as the logistic regression and discriminant analysis (Khandani et al., 2010; Butaru et al., 2016). Butaru et al. (2016) point out that logistic regression, a standard model for estimating credit risk, performs much worse on average than decision trees and random forests. In the implementation proposed by Butaru et al. (2016), for instance, the logistic regression has lower precision and recall, while having a higher false positive rate than decision trees. Brown and Mues (2012) show that random forests perform better than traditional models such as the logistic regression for datasets with high-class imbalances (such as dataset consisting of data on loans). Abellán and Castellano (2017) review the performance of several ensemble classifiers in the context of credit scoring. Zurada (2010) also compares a set of AI algorithms in terms of their predictive performance in the context of credit risk assessment. The author finds that the overall classification accuracy of decision trees significantly outperformed the other models, while also being easier to interpret than other methods (Zurada, 2010). Hens and Tiwari (2012) show

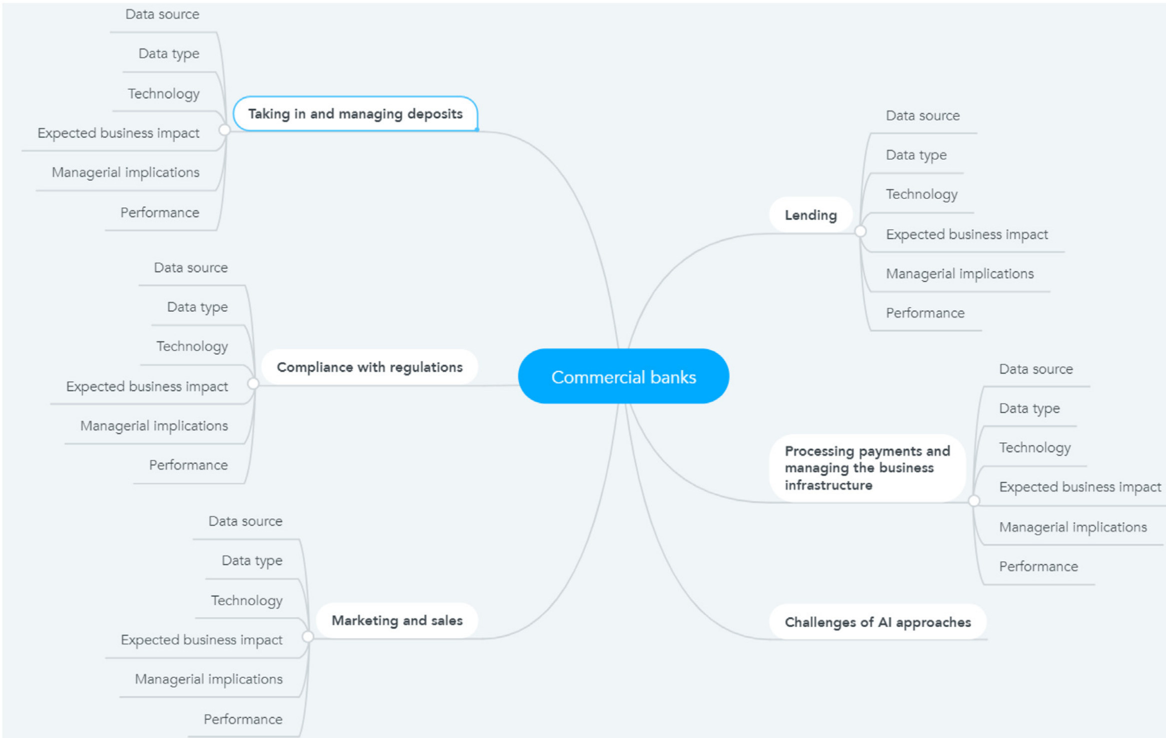

Fig. 1. Linking the dimensions to commercial banks.

that a genetic algorithm predicts credit default better than a set of other methods. Bijak and Thomas (2012) show that classification and regression tree (CART)-based segmentation results in more homogeneous segments than segmentation based on logistic regression. However, the authors also find that better segmentation does not translate into more accurate credit scores (Bijak and Thomas, 2012). In the context of credit scoring, only a single paper was found in which a statistical model outperformed an AI algorithm (Xiong et al., 2013). Also, in the context of predicting the time until a borrower defaults on a loan, the Cox model outperforms neural networks (Sarlija et al., 2009). In the context of credit scoring, the hybrid model proposed by Li et al. (2016) outperforms the logistic regression model. Table 3 shows a summary of the families of algorithms used in lending and the application areas in which they are used.

However, it is essential to note that there is no optimal algorithm. Butaru et al. (2016) indicate that the performance of different algorithms, as well as the best performing algorithm, differ depending on the dataset used in the training and testing process.

4.1.2. Business impact

In addition to technological change, it is also essential to investigate how the usage of AI changes business operations. Khandani et al. (2010) estimate the cost savings to range anywhere between 6% and 25%, but do not go into detail about how, where, and when these cost savings would materialize. Butaru et al. (2016) simulate the cost savings of banks with the help of different AI approaches for different forecasting intervals and find those potential cost savings to range between 9% and 76%. Hens and Tiwari (2012) argue that the lower computational time of an SVM can lead to the implementation being more profitable than that of more accurate classifiers, but do not state how large this difference would be. Chen and Huang (2011), Jadhav et al. (2016), Singh and Aggarwal (2011), Derelioğlu and Gürgen (2011), and Zurada (2010) point to very general benefits of their models but do not go into detail about the business impact of the proposed approaches. The literature shows that the use of AI in credit risk management has the potential for banks to reduce their costs significantly. However, one can also see from the literature that translating the predictive performance of models into changes in business metrics for companies is not an easy task.

AI approaches in banks simultaneously enable commercial banks to extend their business model by servicing new types of customers. Onay and Öztürk (2018) give the example of "LenddoEFL", a P2P lender that uses social network and psychometric data to estimate the creditworthiness of underbanked consumers. Using this data in combination with AI could enable the bank to offer loans to more customers, thereby increasing their customer base and profits.

AI changes lending in two ways. First, AI allows banks to use previously unused types of data to estimate risk credit more accurately. Using new data, such as from social media, might contain useful additional insights into the riskiness of the bank's customers. Second, AI algorithms are more accurate than traditional models for credit risk estimation, making them suitable for risk management. AI can, therefore, be used to replace traditional methods for credit risk estimation. The use of AI in lending can give banks an edge over non-banking competitors. The large amount of data that commercial banks have collected on their customers in combination with banks' experience in credit risk management and their relationships with their clients can give banks a competitive edge against newcomers.

4.2. Processing payments and managing the business infrastructure using AI

Two relevant issues regarding the processing of payments mentioned in our reviewed papers are identifying and preventing fraud and managing the scale of the payment network. AI supports the detection of potentially fraudulent transactions by recognizing patterns in large sets of transactions. Also, AI can

Table 3
Families of algorithms in lending.

Family of algorithms	Use cases	Citations
SVM	• Corporate lending • Loan prediction • Credit rating • Financial statement fraud	Brown and Mues (2012), Hens and Tiwari (2012), Jadhav et al. (2016), Singh and Aggarwal (2011), Tobback and Martens (2019), Xiong et al. (2013), Zhang et al. (2015) and Zurada (2010)
Decision tree	• Predicting credit card delinquencies • Loan prediction • Credit rating • Credit fraud • Financial statement fraud	Bijak and Thomas (2012), Brown and Mues (2012), Butaru et al. (2016), Chrzanowska et al. (2009), Jadhav et al. (2016), Khandani et al. (2010), Xiong et al. (2013) and Zurada (2010)
Neural network	• Corporate lending • Loan prediction • Credit rating • Financial statement fraud • Time-to-default prediction • Credit scoring	Brown and Mues (2012), Chen and Huang (2011), Derelioğlu and Gürgen (2011), Falavigna (2012), Jadhav et al. (2016), Kvamme et al. (2018), Li et al. (2016), Óskarsdóttir et al. (2018), Sarlija et al. (2009), Zhang et al. (2015) and Zurada (2010).
K-nearest neighborhood	• Loan prediction • Credit rating	Jadhav et al. (2016) and Singh and Aggarwal (2011)
Genetic algorithm	• Loan prediction • Credit rating	Hens and Tiwari (2012), Jadhav et al. (2016) and Singh and Aggarwal (2011)
Random forest	• Predicting credit card delinquencies • Loan prediction	Brown and Mues (2012), Butaru et al. (2016), Jadhav et al. (2016) and Óskarsdóttir et al. (2018)
Boosting algorithms	• Predicting corporate bankruptcy • Credit scoring	Brown and Mues (2012), Chrzanowska et al. (2009), Jadhav et al. (2016) and Jones et al. (2017)
Ensemble learning	• Corporate lending	Abellán and Castellano (2017) and Wang and Ma (2012)
Hybrid methods	• Credit scoring	Li et al. (2016)

make the business infrastructure management more efficient by estimating the ATM network usage, making business processes more efficient, or by optimizing the locations of bank branches. This way, AI can have a positive impact on the security and effective supervision of even extensive business networks.

4.2.1. What is AI changing?

4.2.1.1. Making payment networks safer. An essential area for making commercial banks' payment systems safer is the detection of fraud and money laundering. In 2016, the total amount of fraudulent card payments increased to $7.1 billion in the US and $14 billion globally (Jadhav et al., 2016). Kumar et al. (2019) show that random forests and SVMs, in combination with transactional data, can be used to detect cases of elderly exploitation, thereby increasing security. Zhang and Trubey (2019) use decision trees, random forest, SVMs, and artificial neural networks in combination with transactional data to detect money laundering in transactions. Artificial neural networks perform best when class imbalances are large and are least sensitive to changes in the proportion of the target variable (Zhang and Trubey, 2019). Duman and Ozcelik (2011) use a genetic algorithm to detect fraudulent credit card transactions at a Turkish bank. The predictive performance of the models presented by Zhang and Trubey (2019) and Kumar et al. (2019) indicate strong predictive performance, implying that they could be very useful for improving payment system security. Jadhav et al. (2016) showed that AI could be used to detect money laundering in transactions and fraudulent behavior in online banking, among other things. Also, the authors point to a system developed by the US treasury department that can help banks with detecting fraud in cash transactions. By using AI, banks could also detect money laundering in cash and electronic transactions, financial statements, and credit card statements. However, they do not discuss the novelty of the approaches they reviewed and provide limited information on the predictive performance of the algorithms.

4.2.1.2. Managing the scale of the business infrastructure. Literature on managing the payment infrastructure with the help of AI is scarce. Zapranis and Alexandridis (2009) predict the amount of cash withdrawn per day by analyzing a time series of end-of-day balances of ATMs in England using neural networks. Serengil and Ozpinar (2019) predict the cash flows at 6500 ATMs in Turkey with the help of neural networks. Grozin et al. (2015) attempt to predict the amount of cash needed to fill cash dispensers in Russia with the help of SVMs and random forests. Lázaro et al. (2018) go one step further by (1) presenting a method for optimizing the number of cash transports to each branch under investigation and (2) discussing how to integrate the predictions into business processes. Herrera-Restrepo et al. (2016) analyze the efficiency of bank branches with the help of centroid-based clustering. They segment branches based on several branch-related metrics, such as the number of full-time equivalent employees, and a set of output related variables, such as the number of loans given to customers. They subsequently profile the segments of a Canadian bank based on the clusters the branch was assigned to. Specifically, they profile the branches in terms of their overall efficiency and the amount of output (newly opened accounts, mortgages, and transactions) per employee. Using their methodology, bank managers can not only get a clearer view of bank branch performance but also address operational inefficiencies in a more targeted manner.

The data used by the authors mentioned above was provided by commercial banks (Herrera-Restrepo et al., 2016; Grozin et al., 2015; Serengil and Ozpinar, 2019), an unspecified national bank (Lázaro et al., 2018), and the organizer of a conference (Zapranis and Alexandridis, 2009). Given that commercial banks usually have full access to data about the branches and ATMs they operate, the issue of accessing and collecting a sufficient amount of data is trivial from a practical point of view. Table 4 summarizes the families of algorithms that were used for detecting money laundering and fraud in the context of payment systems and the management of the payment infrastructure.

4.2.2. Business impact

Kumar et al. (2019) state that their SVM-based approach reduces costs by reducing the amount of time needed for human evaluation of potentially fraudulent transactions. Even though Jadhav et al. (2016) state how the algorithms they review can be used, they do not evaluate the economic impact that the AI implementation could have on businesses. However, it seems that the AI they reviewed could help commercial banks by stating that the detection of potentially fraudulent activities makes the prevention of damage possible (Jadhav et al., 2016). Also, Tobback and Martens (2019) do not evaluate the economic impact of their implementation but point to the power of AI to detect and prevent money laundering.

Kumar et al. (2019) also point to a number of non-financial benefits of implementing AI for detecting money laundering. First, improving on existing money laundering detection systems reduces the workload of human employees, which enhances the decision quality of human employees. Additionally, better protection of their clients also increases client trust of their institution. Finally, the authors also point to potential reputational damage of money laundering scandals.

Table 4
Families of algorithms used in detecting fraud & money laundering and the management of business infrastructure.

Family of algorithms	Use cases	Citations
Neural networks	• Prediction of cash withdrawals • Fraudulent behavior in online banking	Jadhav et al. (2016), Serengil and Ozpinar (2019), Zhang and Trubey (2019) and Zapranis and Alexandridis (2009)
Random forest	• Fraudulent behavior in online banking • Prediction of cash withdrawals • Detecting elderly financial exploitation	Jadhav et al. (2016), Grozin et al. (2015), Kumar et al. (2019) and Zhang and Trubey (2019)
Clustering	• Detecting money laundering • Analyzing the efficiency of bank branches	Herrera-Restrepo et al. (2016) and Jadhav et al. (2016)
Support vector regression	• Prediction of cash withdrawals and cash deposits	Lázaro et al. (2018)
SVM	• Prediction of cash withdrawals • Detecting elderly financial exploitation	Grozin et al. (2015), Kumar et al. (2019) and Zhang and Trubey (2019)
Decision tree	• Detecting money laundering	Zhang and Trubey (2019)
Genetic algorithm	• Detecting fraudulent transactions	Duman and Ozcelik (2011)

The methods proposed by Zapranis and Alexandridis (2009), Serengil and Ozpinar (2019), and Grozin et al. (2015) help commercial banks with scheduling the maintenance of their ATM network as well as with improving the allocation of money to different ATMs. This means that banks could reduce the maintenance costs of their ATM network while simultaneously increasing revenue. Lázaro et al. (2018) describe how such a system could look like in real life and how business processes need to be adapted to reap the full benefits of AI approaches in practice. This means that using AI approaches for fraud detection and managing the payment infrastructure can benefit banks in terms of increased security, reduced costs, and increased revenue. In turn, this could positively impact the competitiveness of commercial banks.

4.3. Compliance management using AI

When looking at compliance, using AI can help commercial banks with constant monitoring of activities inside the company; semiautomatic processing of new regulations; and detecting fraudulent behavior. Even though the precise monetary payoff is not quantified in the literature, the authors point out that the use of AI can speed up business processes and help with the detection of more types of compliance breaches.

4.3.1. What is AI changing?

As mentioned in Section 2.4, the growing amount of regulations is a challenge for banks. However, Aziz and Dowling (2019) state that AI can help in the context of RegTech by continuously monitoring all activities in a company. Even though Aziz and Dowling (2019) do not describe any algorithms or other technology involved in managing compliance risk in their publication, they do point to two specific uses of AI in compliance management.

Table 5
Family of algorithms used for detecting fraud and money laundering according to Jadhav et al. (2016).

Family of algorithms	Use cases	Citations
Neural network	• Fraudulent behavior in online banking • Financial statement fraud	Jadhav et al. (2016)
Random forest	• Fraudulent behavior in online banking	Jadhav et al. (2016)
Clustering	• Money laundering transactions	Jadhav et al. (2016)
SVM	• Financial statement fraud	Jadhav et al. (2016)
Decision tree	• Credit fraud • Financial statement fraud	Jadhav et al. (2016)

In their first example, Aziz and Dowling (2019) point to audio analysis as well as natural language processing as two technologies that power the detection of non-compliance with regulations by analyzing phone conversations between employees and clients and between employees in real-time. By analyzing internal data such as phone calls made by their employees, commercial banks can detect emerging types of non-compliance before they become actual regulatory breaches or cause damage to clients. The detection enables commercial banks to prevent breaches before they happen.

Aziz and Dowling (2019) and Butler and O'Brien (2019) state that AI can also be used to read and interpret regulatory documents by using natural language processing. Butler and O'Brien (2019) describe an application of AI in which semantic tagging is used to match a regulation to the banks' applicable products and services. This means that there are methods that can be used to ensure that new regulations are implemented in an automated or semi-automated manner.

In addition to analyzing internal firm activities and texts published by regulatory agencies, banks can also use AI to analyze the activities of their customers. Jadhav et al. (2016) point to detecting money laundering and various types of fraud as applications of AI in commercial banks. Since all of the technologies, as well as the application cases mentioned by Jadhav et al. (2016), were already described in Sections 4.2 and 4.3, the current section will not go into detail about what the AI does and how it relates to commercial banking. Table 5 points to the algorithms that were most frequently used in the context of detecting money laundering and fraud detection.

What makes the analysis of regulations in commercial banking challenging is the lack of shared business and regulatory terminology (Butler and O'Brien, 2019). This means that similar products and services could be marketed and sold under different names by different banks. This aspect has major implications for documenting AI in commercial banks. Given that the terminology of individual banks is different from that of the regulator, commercial banks must ensure that they include a description of their products and services that are being analyzed by AI as well as descriptions of business terminology that are used in banks' business processes.

4.3.2. Business impact

Aziz and Dowling (2019) point out that the key advantage of using AI in RegTech is the system's ability to continuously monitor all activities in the company. Butler and O'Brien (2019) point to the option to create a system that processes all new regulations in an automated or partially automated manner. Jadhav et al. (2016) imply that the AI they reviewed could help reduce the amount of money lost to fraud and money laundering. However, neither paper precisely quantifies the monetary impact that proper implementation of AI in regulatory compliance would have.

An important aspect related to the issue of compliance management using AI is the question of how to combine the detection of non-compliance with an employee's right to privacy. Analyzing phone calls of employees could also be seen as misconduct in the eyes of the European General Data Protection Regulation (European Parliament, 2016). This means that commercial banks need to find a balance between compliance management and protecting the privacy of their employees.

Challenges related to privacy also affect areas unrelated to compliance. In order for commercial banks to reap the benefits of AI, employees need to be willing to use AI. If employees perceive the AI as a violation of their privacy, they might not accept the AI and intentionally avoid using tools that incorporate AI. In practice, this could lead to employees turning their company-provided phones off and communicating via their personal cellphones instead. Systems need to be designed in a way that encourages acceptance and use by employees.

4.4. Marketing and sales using AI

When considering marketing and sales, the use of AI enables commercial banks to use more granular data in their marketing campaigns, which can lead to more accurate customer targeting. In turn, this can be used to sell more to customers or to keep customers from taking their deposits to other banks.

4.4.1. What is AI changing?

As mentioned in Section 2.4, commercial banks are facing strong competitive pressures from companies providing almost identical products and services. Given the increase in competition, it is important for commercial banks to retain their current customers while simultaneously increasing their customer base. Martens et al. (2016) provide a novel way to target existing bank customers by analyzing the debit transactions of 1.2 million customers of a large European bank in combination with an SVM. By analyzing the behavioral data of consumers, commercial banks are able to gain insights into the preferences of their customers and are able to predict which customers are most likely to purchase one of two financial products – a pension fund or a long-term deposit plan. They point out that increases in the size of such a granular dataset will lead to substantial gains in the performance of AI-based analyses (Martens et al., 2016). This improvement in the results could result from the data-containing events that are unlikely to occur in any individual but occur somewhat frequently overall. According to Alfaro et al. (2019), BBVA was able to make recommendations to SMEs by using a similar AI. Nie et al. (2011) detect credit card churners for a Chinese commercial bank with the help of decision trees. Shih et al. (2011) use self-organizing maps to cluster and profile bank customers. Based on the cluster profiles, banks can determine which customers are both low risk and high return and are able to design targeted marketing campaigns for their respective customers. This means that extracting customer behavior through observing customers' purchases can give banks the opportunity to design individualized, highly targeted marketing campaigns. If a customer has shown a high-risk appetite through frequent purchases on gambling websites, for instance, a bank could send that customer a promotion for high-risk investments, such as stock options. This means that extracting customer preferences through observing customers' purchases might strengthen the bond between banks and their customers and simultaneously give them an edge against their competitors.

However, the performance of the algorithms seems to depend on the data used. Ładyżyński et al. (2019) did not predict the likelihood of consumers taking out a personal loan with the help of random forest, decision trees, and neural networks sufficiently well for the bank to implement their model. Ali and Arıtürk (2014) show that predicting the churn of customers is possible for banks but that the decision tree model fails to outperform the logistic regression in terms of the area under the receiver operator curve. Therefore, banks will need to test which algorithm best fits their dataset. Table 6 shows the families of algorithms used in marketing and sales.

Table 6
Families of algorithms used in marketing and sales.

Family of algorithms	Use cases	Citations
SVM	• Customer targeting	Ładyżyński et al. (2019) and Martens et al. (2016)
Decision tree	• Churn prediction	Ali and Arıtürk (2014) and Nie et al. (2011)
Neural network	• Churn prediction	Nie et al. (2011)
Random forest	• Churn prediction	Nie et al. (2011)
Clustering	• Customer profiling	Shih et al. (2011)

Based on transactional data, commercial banks (and researchers) can observe the earnings and savings of their customers. Such a granular dataset gives commercial banks and researchers insights into lifestyle choices and behavioral patterns of account holders (Ładyżyński et al., 2019). Incorporating this data in research projects could be highly beneficial for researchers in behavioral finance. Researchers could – for instance – observe the impact of real-life, high-risk behavior on the investment choices of customers.

4.4.2. Business impact

More targeted marketing campaigns can, for instance, be used to either sell more to existing customers or keep customers from leaving the company (Alfaro et al., 2019; Martens et al., 2016; Nie et al., 2011). For instance, Alfaro et al. (2019) state that sales made to SMEs by branches that were equipped with AI were twice as high as the sales made by offices without AI. They estimate that AI implementation leads to approximately 1.7 million in additional sales and about 2000 new SME clients. Even though Martens et al. (2016) refrain from giving a precise numeric description of the economic impact of their AI, they highlight that the proposed method was able to identify customers that bought the product with much higher accuracy than the traditional targeting method. AI can help commercial bank employees approach customers with offers that customers are more likely to accept, thereby benefiting both the customer and the bank.

4.5. Deposit/account management using AI

No relevant papers focusing mainly on AI applications to deposit management in commercial banks were found. However, there are several papers that were found in the context of this review that have a link to deposit management.

4.5.1. What is AI changing?

Martens et al. (2016) present a method for identifying customers that might be willing to purchase a long-term deposit plan using the technology explained in Section 4.4. Even though Martens et al. (2016) see the main contribution of their paper in marketing, it also has implications for deposit management. Specifically, commercial banks can use the method for increasing the number of long-term deposits from their customers, thereby decreasing the banks' reliance on credit.

Lázaro et al. (2018) present a way for commercial banks to forecast the number of cash withdrawals from and cash deposits to ATMs and bank branches and to optimize the logistics behind those cash withdrawals and deposits. We refer to Section 4.2 for the technological details of the approach presented by Lázaro et al. (2018).

4.5.2. Business impact

Even though neither Martens et al. (2016) nor Lázaro et al. (2018) consider the impact on managing and taking deposits, their approaches can also have business implications for this area. Specifically, convincing customers to deposit money for the long term reduces banks' reliance on outside creditors. Optimizing the branch and ATM network used to acquire cash deposits can lead to lower costs associated with taking and managing deposits.

Alfaro et al. (2019) mention that BBVA used clustering in combination with their customer's payment transactions to give their customers individualized budgeting advice. Even though they do not describe how this service impacts that bank or their customers, it could have a significant positive impact on people with limited financial knowledge.

4.6. Challenges of AI in commercial banks

Using AI in commercial banks does not only come with benefits. The literature highlights several challenges when implementing AI in commercial banks. Using AI in commercial banks presents researchers with a combination of challenges that make the implementation of AI a unique challenge.

4.6.1. Realization of technological advantages

Scholars conclude that transferring the technical features and advantages discussed in academic settings into practice is not trivial. The selection of the right data and the right algorithm seems to be a challenge. Specifically, scholars point to the availability of skilled staff (Aziz and Dowling, 2019), the predictive performance of algorithms (Butaru et al., 2016; Jadhav et al., 2016) and the data properties as being particularly challenging (Bücker et al., 2013; Butler and O'Brien, 2019; Jadhav et al., 2016; Khandani et al., 2010; Kvamme et al., 2018; Onay and Öztürk, 2018; Sigrist and Hirnschall, 2019; Zapranis and Alexandridis, 2009; Zurada, 2010). As described in Section 4.1, the performance of AI varies, depending on the choice of data source and algorithm of bank decision-makers.

4.6.2. Embedding AI approaches into organizational practice

An important aspect of technology diffusion is the embedment into organizational practice. In contrast to radical process reengineering, we found examples in which AI leads to small adaptions of business processes. Butaru et al. (2016), for example, investigate AI in the context of predicting credit card delinquencies and the effect of setting different thresholds for the adjustment of consumer credit lines. However, apart from these small changes in the process logic, they do not investigate which implications AI integration can have on the human and organizational structure of the bank. One paper specifically addressed the issue of integrating AI into business processes, which also shows that AI in commercial banks is a future topic. Evidence from other industry sectors suggests that the changes can be significant. Specifically, as AI offers higher degrees of automation, AI integration into business processes and the definition of the roles and responsibilities of employees need to be investigated. The interaction of machines or employees with customers, for instance, could be particularly important in situations in which AI does not have an adequate answer to customers' questions or when AI recommendations have an unintended negative effect on the lives of customers.

4.6.3. Ensuring user acceptance by making AI transparent

Many of the investigated papers consider the topic of introducing AI into commercial banks a challenge because current AI approaches are not sufficiently explainable, interpretable, and reproducible (Aziz and Dowling, 2019; Butaru et al., 2016; Butler and O'Brien, 2019; Jones et al., 2017; Kvamme et al., 2018; Zurada, 2010). Butaru et al. (2016) state that the decision-making process of many AI algorithms are highly untransparent – a challenge that is referred to as the black box problem of AI (Adadi and Berrada, 2018) – and that this attribute of AI algorithms is a barrier for adoption. Balancing explainability, interpretability, and transparency with potential performance improvements is an ongoing issue in the literature.

4.6.4. Trust that technology ensures privacy

Additionally, the limited trust in AI recommendations and in the proper handling of data is a frequently mentioned challenge. Martens et al. (2016) state that privacy is always an issue when customer data is analyzed. When collecting and analyzing employee data, such as the analysis of phone conversations described by Aziz and Dowling (2019), privacy considerations need to be considered as well. Handling the related legal and ethical issues in a way that makes users trust the respective technology is an important topic in the literature. For commercial banks, this means that they need to think hard about how they can get their customers and their employees to trust their AI.

4.6.5. Documentation to comply with legal requirements

The proper documentation of AI is another challenge in the analyzed papers. Documentation is challenging for two reasons: the high dependence of AI approaches on the data (as described in Section 2.3) and the lack of shared business and regulatory terminology in the banking industry (described in Section 4.3) (Barocas and Selbst, 2016; Butler and O'Brien, 2019).

Existing documentation approaches for IS focus on algorithms, interfaces, etc., but not on data used to train a specific algorithm. However, the training data sets determine the behavior of AI algorithms. Barocas and Selbst (2016) point out that using biased data in the AI training process might cause the AI to make the same mistakes as previous human decision-makers. This could lead to undetected discriminatory decisions, for instance Barocas and Selbst (2016). Butler and O'Brien (2019) also point out that the same product might be referred to differently by different commercial banks and regulators. Aziz and Dowling (2019) point out that black box systems can hardly be adequately overseen, which could cause regulatory problems for commercial banks and is a barrier for adoption.

Additionally, documenting AI to comply with regulatory demands may require commercial banks to include information about the training data, data cleaning processes, and AI-involved products and services. However, the data perspective is wholly ignored in international standards, such as the one described by Hayhoe (2012). Research needs to investigate how information about data and processes can and should be integrated into AI documentation.

5. A research agenda for behavioral finance

This section presents a research agenda for behavioral finance. Glaser et al. (2004) state that "behavioral finance research is either focused on individual behavior [...] or on the implications for financial market outcomes". In the previous sections, the authors have reviewed many papers that investigate the behavioral patterns of three groups: customers; employees; and other stakeholders such as regulators or auditors.

When looking at individual investors, behavioral finance typically investigates the impact of psychological traits, such as Norman's (1963) 'Big Five', gender, preference, and risk taking propensity as described by Jackson (1976); or human biases, such as conservativism and mental accounting, on financial decision-making and financial wellbeing (Anic and Wallmeier, 2020; Brüggen et al., 2017; Durand et al., 2008; Glaser et al., 2004). Behavioral finance literature also investigates how financial information can be made understandable for individual investors (Agnew and Szykman, 2005). Additionally, literature in behavioral finance investigates how investors' behavioral biases can be mitigated, for instance, in the literature on robotic advisors in wealth management (Bhatia et al., 2020).

Customers' acceptance of and intention to use new financial products, as well as the attractiveness of complex financial products, also play an important role in the literature on behavioral finance (Anic and Wallmeier, 2020; Chiou and Shen, 2012; Jiménez and Díaz, 2019; Martins et al., 2014; Phoon and Koh, 2017). Jiménez and Díaz (2019) investigate the effect of different characteristics (including educational level, gender, being self-employed, and ATM usage) on the intention to use internet banking. Chiou and Shen (2012) focus on determinants for the acceptance of online financial services, and Brenner and Meyll (2020) point to a set of factors that are important for the acceptance of robotic advisors.

A topic of particular interest is the role of employees in the design of financial services. In the context of wealth management, for instance, Salampasis et al. (2017) point to employees' ability to connect with investors on an emotional level as a major advantage and argue that employees should always be involved in making investment decisions. Bhatia et al. (2020) also point out that humans are very skilled at understanding investors' expectations. In this regard, behavioral finance literature focuses on employees' ability to emotionally connect with investors.

Behavioral finance also investigates the behavior and behavioral biases of other stakeholders in financial markets. Nofsinger (2005) argues for a strong relationship between general levels of optimism/pessimism in society and the stock market. Du and Budescu (2018) investigate the degree of financial analysts' overconfidence. Nguyen et al. (2018) find that optimistic CEOs buy back more stocks in the context of a re-purchasing program than their non-optimistic counterparts. Gandhi et al. (2019) argue that bank managers can also engage in "window dressing behavior" to hide illegal or unwanted behavior. Behavioral finance literature also points to the role of the regulator in finance. Zheng and Ashraf (2014) indicate that regulatory pressure can restrict the behavior of banks, for instance, by putting limits on their lending and dividend paying behavior. Anic and Wallmeier (2020) point out that due to European legislation, financial service providers need to provide information about the products and services that they offer. Gandhi et al. (2019) point out that regulators may benefit from using more sophisticated models, such as those based on sentiment in annual reports, to predict distress in banks. In this regard, literature in behavioral finance focuses on investigating optimism, pessimism, and window dressing in other stakeholders.

In this section, the authors will present future research avenues for behavioral finance resulting from the insights derived from this literature review.

5.1. Exploring opportunities and barriers of using AI and transactional data

With an intimate, highly granular dataset, researchers and banks can infer personal details about their customers. Combining a dataset consisting of credit card transactions with AI, for instance, can give researchers and banks insight into the behavioral patterns and lifestyle choices of card holders Ładyżyński et al. (2019). Ładyżyński et al. (2019) and Martens et al. (2016) show how banks can use the combination of transactional data and AI in direct marketing, and Alfaro et al. (2019) state that BBVA was able to provide its customers with an AI-based budgeting tool.

Extracting behavioral information and lifestyle choices from transactional data using AI also has implications for behavioral finance. Using AI, researchers could, for instance, get a more granular view on how Norman's (1963) 'Big Five' personality traits can materialize in our daily purchases and financial decisions. In this regard, it might be very interesting to design experiments to investigate how customers, employees, and stakeholders adapt their behavior (represented in the data) to hide their "real" personality.

Additionally, transactions may contain clues about what mental operations individuals and households use to organize their financial activities. Using AI in combination with transactional data could therefore provide behavioral and experimental finance researchers with more detailed insights into mental accounting. AI could therefore be the solution to Gippel's (2015) call for methods to explain behavior using other than traditional expectation models. Researchers in behavioral finance need to explore how AI can be used to explain the different forms of mental accounting, how they can be combined with existing methods, and whether these methods are accurate.

5.2. Attractiveness of and intention to use AI-based financial services

Literature on behavioral finance also investigates customers' intention to use new financial products and tools. Jiménez and Díaz (2019) analyze how certain factors affect the intention to use internet banking. Several researchers point to transparency, immediate availability, and lower vulnerability to conflicts of interest as important factors for investors' intention to use algorithmic advisors (Brenner and Meyll, 2020; Phoon and Koh, 2017). However, no research on what factors contribute to the attractiveness of and the intention to use other AI-based products could be found. However, as shown in our review, AI-based products are coming to the market, and research in this direction seems promising. Researchers in behavioral and experimental finance could, for instance, explore customers intention to use such services, to share data, to trust AI-based decisions, or to manipulate data.

An important related question is how outputs of AI-based financial services need to be presented to customers. The black-box character is a main adoption barrier in this regard. Adadi and Berrada (2018) provide several different methods for explaining AI models, and the proposed methods are highly technical and complex. However, Anic and Wallmeier (2020) argue that information around complex (financial) products needs to be "intuitive and easy to comprehend" for the product to be perceived as attractive. Behavioral and experimental finance researchers need to investigate how AI results and descriptions must be presented so that customers develop trust and finally perceive the product as attractive.

5.3. AI and the role of employees in consulting customers

The behavioral finance literature considers employees' ability to connect with other human beings as a major benefit for investors. Yet, given the increasing use of AI in financial services, the division of labor between AI and humans and particularly the role of employees need to be redefined (Salampasis et al., 2017). Employees could, for instance, focus on what Brüggen et al. (2017) define as "interventions", such as financial education and counseling. Humans may also be better than AI at assisting people with what Brüggen et al. (2017) call "life events", such as divorce, the death of a parent or a spouse, or losing one's job. Employees' emotional intelligence could help them relate to people in such situations more easily than AI. Apart from that, banks may be barred from analyzing data on many of the personal life events described by Brüggen et al. (2017).

From a research perspective, it seems interesting to investigate AI's role in consulting situations. How can AI-based decision support assist employees in consulting situations, and how much do employees rely on AI recommendations versus their intuition? Some research indicates that AI use could lead to employees performing better than without AI (Salampasis et al., 2017). However, it needs to be investigated up to what point employees benefit from the use of AI and from what point their performance decreases. It needs to be ensured that human emotional intelligence is maintained and AI systems are designed in a way that employees are still using their intuition. Behavioral and experimental finance should investigate this relation.

5.4. Using AI to analyze the behavior of financial analysts and decision-makers in banks

By analyzing external data, such as calling and texting behavior, social media data, or utility or phone bill payment data using AI, lenders are able to predict the creditworthiness of people they have never met (Onay and Öztürk, 2018; Óskarsdóttir et al., 2018). Behavioral finance researchers have also started to use similar methods. Gómez Martínez et al. (2019), for instance, present an algorithmic trading system that is based on extracting investors' moods from social media or news. Gandhi et al. (2019) analyze annual reports to predict financial distress in US banks. This shows that behavioral and experimental finance researchers now have more options to investigate the behavior of decision-makers inside companies. This also means that researchers could use experimental methods to investigate more behavioral patterns in financial data. For instance, researchers could attempt to detect window dressing in a bank's transactions. Additionally, also it seems promising to use AI to analyze strategies that financial analysts and decision-makers use to hide their behavioral patterns.

Also, Salampasis et al. (2017) argue that the "investment decision-making process will now be reflected within a spectrum of algorithms, rationality, irrationality, ethical decision-making and behavioral management elements". This means that investors could choose between a variety of algorithms and get a more personalized investment experience. Researchers could run experiments to investigate how this personalization could most benefit investors. Further, it seems promising to use experimental methods to analyze the behavior of decision-makers in companies and research methods to measure and reduce overconfidence and excessive optimism based on the analysis of internal data.

5.5. How does AI need to be documented?

Bhatia et al. (2020) point out that AI can also be used to exploit investors. For instance, an AI expert involved in the implementation of an AI system can steer investors toward investment opportunities of his choosing or use a biased dataset to train the AI. This would most likely result in an AI that will make biased recommendations and could harm investors (Bhatia et al., 2020). Diakopoulos (2016) argues that accountability in the context of AI can be increased by explaining AI models and keeping track of the data the AI was trained on, any human involvement in the AI development process, the way the AI makes its inferences, and how and where the AI is used in business processes. From a regulatory and legislative point of view, it would be interesting to know how effective such measures are in preventing AI experts from manipulating and harming investors. Researchers in behavioral finance can investigate how documenting the attributes described by Diakopoulos (2016) influences the behavior of AI experts involved in the creation of AI-based financial services. For instance, experiments on different documentation approaches and their effects on biases in and the quality of AI-based financial services seem promising.

6. Conclusion

As this paper has shown, AI can be used in all core business areas of commercial banks. In the context of lending, AI can be used to make accurate predictions using previously unused data types. By analyzing these unused data types, credit risk models become more accurate, profits can be increased, and new types of customers can be serviced. Using AI for detecting fraud and money laundering can make payment processing safer for customers. AI can also be used to predict cash demand and reduce operating costs for ATM and branch networks. Using AI in compliance can help banks process the increasing amount of regulations faster, detect suspicious activity among their employees, and report suspicious client activity. In marketing and sales, AI can recommend relevant products for customers and help with more accurate targeting of customers. In the deposit and account management, AI can help commercial banks by reducing the cost of cash deposits and by providing new services to customers.

We expect that these applications of AI can have significant benefits for commercial banks in the future, but only if several challenges are addressed. Improved risk management while using AI can lead to higher profits if explainability can be ensured and the AI model can be documented in a way that legal requirements are fulfilled. With the help of AI, the efficiency of marketing activities can be increased, and compliance management can be made more efficient, but only if the challenge of privacy in the context of AI can be resolved. More efficient management of the business infrastructure can reduce costs for the bank, but only if AI can be integrated into the business processes.

During the review, the authors also realized that there was limited research on how to use AI in managing and taking deposits as well as in processing payments and managing the payment infrastructure. Existing papers show that using AI in the respective areas does have benefits. However, the literature does not cover all application cases. Alfaro et al. (2019) state that BBVA manages to find optimal locations for their branches, which led to significant cost savings for BBVA. However, additional publications on how to apply AI for finding optimal locations of branches were not found in the context of the review.

Reflecting on the results of the review in light of the literature on behavioral finance also yielded several exciting avenues for further research. Several papers reflected on how AI can be used to explore the psychological and behavioral patterns of investors. The authors also note that more research needs to be done on determining the factors that contribute to the attractiveness of and customers' intention to use AI-based financial services. Additionally, research on the interaction between employees and AI in daily business and decision situations seems promising. The authors also point to interesting avenues for further research on investigating the behavior of decision-makers inside companies. Additionally, experiments on how to measure and reduce overconfidence and excessive optimism based on the analysis of internal data are recommended. Finally, more research on suitable documentation of AI-based services for regulators also seems promising.

The authors also wanted to point out that research on AI applications to commercial banks can benefit from taking a look at how AI was applied outside of commercial banking. Abbasi et al. (2012), for instance, present a meta-learning framework for detecting financial fraud in publicly available data on companies in the US. The authors discuss the potential impact of fraud on stock owners. However, the impact on lenders or bondholders is not discussed. Weterings et al. (2019) use deep-learning methods and attention models to explain customer activation in the context of a large pension insurance company in the Netherlands. Miller and Töws (2018) use random forests to estimate loss given

Table A.1

	Zurada (2010)	Hens and Tiwari (2012)	Tobback and Martens (2019)	Zhang et al. (2015)	Singh and Aggarwal (2011)
Lending	Brown and Mues (2012)	Jadhav et al. (2016)	Bijak and Thomas (2012)	Butaru et al. (2016)	Xiong et al. (2013)
	Chrzanowska et al. (2009)	Khandani et al. (2010)	Óskarsdóttir et al. (2018)	Chen and Huang (2011)	Derelioğlu and Gürgen (2011)
	Jones et al. (2017)	Falavigna (2012)	Li et al. (2016)	Sarlija et al. (2009)	Kvamme et al. (2018)
	Abellán and Castellano (2017)	Wang and Ma (2012)			
Processing payments and managing business infrastructure using AI	Kumar et al. (2019)	Serengil and Ozpinar (2019)	Zapranis and Alexandridis (2009)	Jadhav et al. (2016)	Zhang and Trubey (2019)
	Duman and Ozcelik (2011)	Lázaro et al. (2018)	Herrera-Restrepo et al. (2016)	Grozin et al. (2015)	
Compliance management using AI	Butler and O'Brien (2019)	Aziz and Dowling (2019)	Jadhav et al. (2016)		
Marketing and sales using AI	Martens et al. (2016)	Ali and Arıtürk (2014)	Ładyżyński et al. (2019)	Shih et al. (2011)	Nie et al. (2011)
Deposit/Account management services using AI	Martens et al. (2016)	Lázaro et al. (2018)	Alfaro et al. (2019)		

default for leases. Even though leases are different from mortgages and collateralized loans, "the basic idea can be adjusted in general to estimate the [loss given default] of other instruments such as collateralized loans and in particular mortgages" (Miller and Töws, 2018). The authors of this paper would encourage researchers to link the mentioned cases of AI applications to commercial banks.

CRediT authorship contribution statement

Florian Königstorfer: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. **Stefan Thalmann:** Conceptualization, Project administration, Resources, Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Papers analyzed in this literature review

See Table A.1.

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