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# POTENTIALS AND CHALLENGES OF ARTIFICIAL INTELLIGENCE IN FINANCIAL TECHNOLOGIES

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*Research full-length paper*

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## Abstract

*Artificial Intelligence (AI) made disruptive progress over the last years, becoming a key technology across industries. In particular, AI offers novel distinctive potentials for intelligent services in financial technology companies (financial technologies). However, given the potential of AI and its associated benefits, the question arises why financial technologies fail to leverage the full potential of AI. Drawing on existing literature, this paper elaborates on the potential and challenges associated with AI in the financial sector. This paper makes two key contributions: First, we discover the present challenges in literature to demonstrate the need for explainable AI. Second, we reveal the lack of guidance for applying explainable AI in financial technologies. We derive recommendations for research, policy, and practice and argue for the increased elaboration of legal frameworks for the responsible use of AI.*

*Keywords: Artificial Intelligence, Explainable Artificial Intelligence, Financial Technology.*

## 1 Introduction

Artificial Intelligence and Machine Learning algorithms are becoming critical digital transformation technologies, with researchers heralding the next most crucial general-purpose technology (Buxmann et al., 2021). Since the number of application areas and use cases has increased, the economic value of AI has hardly been doubted anymore (Asatiani et al., 2021; Maass et al., 2018). At the same time, more reports of dangers associated with using more inscrutable AI, also known as the “black-box” phenomenon, are emerging. As highly complex and increasingly opaque mathematical constructs (e.g., Neural Networks) can process extensive data sets, they lack transparency, interpretability, fairness, and responsibility (Bauer et al., 2021). Therefore, the results are often neither verifiable nor explainable. Consequently, it is challenging for users and operators to trust the results of AI. This circumstance poses companies with significant challenges in meeting regulatory requirements and averting economic losses, reputational damage, and legal troubles. Moreover, opaque AI complicates its appropriate use in areas where social responsibility, trustworthiness, accountability, and security are critical (e.g., Hadji Misheva et al. (2021), Tjoa and Guan (2021)).

In this vein, the explainability of AI has become a crucial issue in various fields. Explainable AI (XAI) aims for transparent and for humans understandable AI algorithms and to explain why the algorithm has come to the corresponding result, but XAI does not automatically ensure responsible use of AI (Barredo Arrieta et al., 2020). The call for explainability is also noticeable in the financial technology sector, where an increasing integration of AI in value creation can be observed (Bussmann et al., 2020). Financial technologies also referred to as FinTechs, are defined as "[…] *the usage of digital technologies such as the Internet, mobile computing, and data analytics to enable, innovate, or disrupt financial services*" (Gimpel et al., 2018). On the upper side, AI systems offer the enormous economic potential for the financial technology sector, such as automation and increased efficiency. On the downside, wrong decisions may seriously impact many stakeholders. Noteworthy that using complex AI to support critical decision-making raises ethical, legal, and practical concerns (Asatiani et al., 2021). However, it is not easy to trace how a decision was eventually reached using black-box models, e.g., contradicting EU General Data Protection Regulation (European Union, 2016).

To address these concerns and problems and meet the general requirements of AI across domains, research is already addressing the interpretability and explainability of AI to improve the existing insights and applications (Lossos et al., 2021). For example, in the finance sector, there are studies on the comprehensibility of credit scoring (Bussmann et al., 2020; Demajo et al., 2020; Hadji Misheva et al., 2021) and anti-money laundering (Kute et al., 2021). Accordingly, initial efforts are in place to implement the concept of XAI in the finance sector and thus contribute to quality assurance in practice. However, it is unclear to what extent XAI can ultimately address the challenges of AI limited to specific use cases, while a bigger picture of the potential of XAI in financial technologies is missing. Therefore, it can be added that some literature reviews (e.g., Königstorfer and Thalmann, (2020); Milana and Ashta (2021)) already exist, but they take a somewhat narrower perspective, and none of them focus specifically on XAI. To address this gap in research and practice, we formulate our research questions (RQ) as follows:

*RQ1: What are the potentials and challenges of AI in financial technologies?*

*RQ2: How can the use of XAI contribute to leveraging AI´s potential in financial technologies?*

To answer the research questions, we conduct a structured literature review and systemize studies with different focuses and perspectives on AI, the potentials and challenges, and XAI in financial technologies to provide a sound basis. We subsequently structure AI challenges in financial technologies to analyze how XAI might mitigate or solve them. This allows us to derive implications and recommendations for future research, practice, and policy in a highly data-centric field of financial technologies. Unlike existing works on XAI in general focusing on technical details such as (Barredo Arrieta et al., 2020), (Bussmann et al., 2020), and (Kute et al., 2021), we approach the research question through a more practice-oriented perspective. Our findings reveal that XAI might be a promising approach to tackling AI's existing limitations and challenges in financial technologies, not limited to specific use cases studied in the literature. In a highly regulated field of financial technologies, the rapid elaboration of legal frameworks for the trustworthy use of AI might be necessary for XAI´s diffusion. We also map and discuss the challenges of AI with the approach of XAI. The remainder of this study is organized into four sections: Section 2 provides a basic understanding of the following work and summarizes the theoretical background. Section 3 presents the methodological approach of the structured literature review. Section 4 discusses the results derived from literature and highlights recommendations for action before presenting the discussion and conclusion in section 5, outlining limitations and further research.

## 2 Foundations

AI is becoming increasingly important as a core technology for business and society and is already being used in diverse sectors such as medical diagnostics, optical character recognition, autonomous driving, industrial applications, and financial services (Brynjolfsson and Mitchell, 2017; Kaymakci et al., 2021; Fabri et al., 2019). By leveraging AI, companies are trying to gain competitive advantages in speed, accuracy, cost reduction, or efficiency. AI describes a combination of new technologies, such as machine learning, natural language processing or cognitive computing, and mathematical or statistical methods or processes (Milana and Ashta, 2021; The Finance Innovation Lab, 2018). The goal of developing and using AI is to imitate intelligent human behavior using learning techniques (Shivkumar and Nihaal, 2017; Bredt, 2019).

Due to AI's potential, companies face a vast transformation (Deshpande, 2020). Product and service quality improvement due to advanced information and communication are expected to lead to faster and more precise action. Additionally, increasing computing power allows for handling an ever-increasing amount of data (Ashta and Herrmann, 2021; The Finance Innovation Lab, 2018). This enables increasing the scalability of business models or products and eliminating human errors (Shivkumar and Nihaal, 2017; Bredt, 2019). Ultimately, AI research increases innovation and leads to new options in business models, leading to increased profits (Bredt, 2019). Financial companies are responding to this upheaval with the growing integration of AI, giving rise to new types of financial technologies (Cheng et al., 2021; Cao et al., 2020a). AI systems are already in use for some applications related to financial companies: Personalized offers & investment strategies (e.g., Shivkumar and Nihaal, 2017), robo-advisor for automated identification of risk preferences (e.g., Deshpande (2020)), algorithmic trading for automatization of trading strategies without human interaction and intervention (e.g., Milana and Ashta (2021), chatbots for automated customer interaction (e.g., Shivkumar and Nihaal (2017)), data-driven, automated assessment of customer's creditworthiness (e.g., Giudici (2018)), and automated fraud detection and anti-money laundering (e.g., Kute et al. (2021)).

However, confidence and trust in the application of AI in financial technologies have not yet reached the general population. Thus, people who are not technology-savvy tend to reject these applications and prefer traditional consulting services (e.g., counter in banks and alternative investments). Consequently, a widespread application of AI and leveraging its potential is lacking. The opacity and unclear traceability of the AI outputs causes mistrust and, thus, lead to the rejection of AI. This is also known as the "black-box" problem (Wenninger et al., 2022). This reflects in the costly phenomenon known as algorithm aversion: Evidence-based algorithms predict the future more accurately than human forecasters, but human forecasters are more often preferred to a statistical algorithm (Dietvorst et al., 2015). AI research is encountering this trend with the approaches of XAI (Asatiani et al., 2020). The idea behind XAI is to provide an additional comprehensible explanation for decision-making. Currently, however, there is no general agreement on how explainability is defined, and there are few approaches to implementation (Asatiani et al., 2020; Bonacina, 2017; PwC, 2018; Demajo et al., 2020). Developing a unified understanding of explainability and exploring the potential of XAI in financial technologies is thus essential to deploying AI broadly.

## 3 Methodological Approach

To investigate how XAI contributes to leveraging AI in financial technologies, we based our research on a comprehensive review of the existing literature, following Webster and Watson (2002). With this literature review, we specifically aim to summarize, structure, and critically examine the potential and challenges of AI in financial technologies. In this vein, we proceed in four steps: (a) identify relevant literature, (b) structure the identified literature by developing a coding scheme, (c) analyze the literature to elaborate potentials and challenges to derive contributions for action, and (d) conduct a discussion to argue for the increased elaboration of frameworks for trustworthy use of AI. We aimed to identify papers applying two significant elements to various databases: "artificial intelligence" and "financial technology”. As literature sources, we chose databases with different focus areas and research scopes to ensure a balanced mix of engineering, technical, academic, and computer science or information systems perspectives and searched in journals and conferences. We derived 964 results, displayed in Table 1.

| | | | |
|---|---|---|---|
| EbscoHost | 77 articles | SpringerLink | 223 articles |
| IEEE Xplore | 73 articles | Wiley | 144 articles |
| ScienceDirect | 344 articles | JSTOR | 103 articles |

*Table 1. Results of the literature search*

After carefully screening the title, keywords, and abstract (Webster and Watson, 2002) regarding their linkage to either potentials and challenges of AI or XAI in financial technologies, we applied a forward-backward search. To enlighten the practical nature of AI and XAI in financial technologies, we conducted an additional web search for whitepapers that have not been addressed in the scientific literature. This led to our final set, including 53 relevant papers encompassing current debates, theories, and reviews on using AI or XAI in financial technologies.

| Study focus (53 papers) | Literature |
|---|---|
| Financial technology (45 papers) | Ashta and Biot-Paquerot (2018); Ashta and Herrmann (2021); Belanche et al. (2019); Bredt (2019); Bussmann et al. (2020); Butler (2020); Cao et al. (2020a); Cao et al. (2020b); Chen and Storchan (2021); Cheng et al. (2021); Couchoro et al. (2021); Cunha et al. (2021); Das (2019); Demajo et al. (2020); Deshpande (2020); Donepudi (2017); Dubey (2019); Galvin et al. (2018); Giudici (2018); Hadji Misheva et al. (2021); Hodson (2021); Kute et al. (2021); Lagna and Ravishankar (2021); Lin et al. (2021); Luo et al. (2022); Machkour and Abriane (2020); Maiti et al. (2021); Marqués et al. (2021); Milana and Ashta (2020); Milana and Ashta (2021); Nizioł (2021); Nosova et al. (2021); OECD (2021); Oliveira and Ruiz (2021); Pourhabibi et al. (2020); PwC (2018); PwC (2020); Shivkumar and Nihaal (2017); Spence (2021); Stahl (2022); Suryono et al. (2020); The Finance Innovation Lab (2018); Vedapradha and Ravi (2018); Zhang et al. (2021) |
| Artificial intelligence (37 papers ) | Adadi and Berrada (2018); Asatiani et al. (2021); Asatiani et al. (2020); Ashta and Herrmann (2021); Barredo Arrieta et al. (2020); Belanche et al. (2019); Benbya et al. (2021); Bonacina (2017); Bredt (2019); Bussmann et al. (2020); Cao et al. (2020a); Chen and Storchan (2021); Couchoro et al. (2021); Das (2019); Demajo et al. (2020); Deshpande (2020); Donepudi (2017); Galvin et al. (2018); Giudici (2018); Hadji Misheva et al. (2021); Kute et al. (2021); Milana and Ashta (2021); Nizioł (2021); OECD (2021); Oliveira and Ruiz (2021); Pourhabibi et al. (2020); PwC (2020); PwC (2018); Shivkumar and Nihaal (2017); Stahl (2022); Suryono et al. (2020); The Finance Innovation Lab (2018); Trocin et al. (2021); Vedapradha and Ravi (2018); Zhang et al. (2021) |
| Explainable artificial intelligence (17 papers ) | Adadi and Berrada (2018); Asatiani et al. (2021); Asatiani et al. (2020); Barredo Arrieta et al. (2020); Benbya et al. (2021); Bonacina (2017); Bussmann et al. (2020); Chen and Storchan (2021); Demajo et al. (2020); Hadji Misheva et al. (2021); Kute et al. (2021); OECD (2021); Oliveira and Ruiz (2021); PwC (2018); Stahl (2022) |

*Table 2. Classification of the relevant literature*

In the second step, we screened the paper’s titles, abstracts, and keywords to fit the scope mentioned above in our study. As selection criteria, we defined a solid relation to the intersection of the application of AI in an economic environment while addressing their potential and challenges. We excluded duplicates and articles that did not refer to the financial technology industry, AI, or XAI. Furthermore, we excluded all articles published in languages other than English. After performing a forward and backward search, the final set includes 53 relevant papers. Subsequently, we thoroughly read and discussed each paper. We structured the articles in a concept matrix (s. Table 2) to quantitatively assess the literature search. We mapped the papers non-exclusively to the study focusing on financial technology, AI, and XAI. Forty-five papers were directly financial technology-related, and 37 financial technology-related articles were also AI-related. 17 of the 45 financial technology-related articles were directly related to XAI. In step three, following this quantitative assessment and findings in the extant literature, we elaborate on the potentials and challenges of AI in financial technologies. In the fourth step, we discussed our results to shed light on the challenges of AI in financial technologies and derive recommendations for research, policy, and practice.

# 4 Findings and Contribution

Temporarily classifying the literature, we see a strong tendency for more publications in the last two years. While only 14 papers stem from 2017 to 2019, 39 papers are published from 2020 to today. This emphasizes the relatively new field of research at the intersection of AI and XAI usage in financial technologies. Typical for new research fields is that the community is not streamlined, and there is neither a clear path for research nor a structured overview of the status quo.

## 4.1 Potentials of using AI in financial technologies

Analyzing literature, we categorize potentials in three dimensions: (1) Economic and entrepreneurial potentials, (2) technological, and (3) societal potentials. The first dimension focuses on potentials that directly influence the economic success of existing or new businesses. The second dimension focuses on individual services or technological aspects, while the third dimension deals with AI's societal effects, such as the influence on jobs. Table 3 briefly summarizes AI's potential in financial technologies and relates them to internal or external/customer references. The internal reference considers aspects of the company that uses AI, while the external/customer reference refers to the effects on customers and external stakeholders. However, potentials may not be mutually exclusive to some dimensions.

<table>
<tr><th></th><th></th><th>Internal reference</th><th>External/customer reference</th></tr>
<tr><td rowspan="13">Potentials</td><td rowspan="5">Economic & entrepre-neurial</td><td>Product quality and productivity</td><td></td></tr>
<tr><td>New business models</td><td></td></tr>
<tr><td>Innovation</td><td></td></tr>
<tr><td></td><td>Improved services</td></tr>
<tr><td>Regulation</td><td></td></tr>
<tr><td rowspan="6">Technological</td><td colspan="2">Modern AI-technologies</td></tr>
<tr><td colspan="2">Chatbots</td></tr>
<tr><td colspan="2">Robo-advisors</td></tr>
<tr><td colspan="2">Algorithmic-trading</td></tr>
<tr><td>Big data</td><td></td></tr>
<tr><td colspan="2">Fraud detection</td></tr>
<tr><td rowspan="2">Societal</td><td></td><td>Fairness & trust</td></tr>
<tr><td></td><td>Creative and value-oriented jobs</td></tr>
</table>

*Table 3. Potentials for aI in financial technologies*

#### 4.1.1 Economic & entrepreneurial potentials

First, product quality and productivity are positively affected by AI (Shivkumar and Nihaal, 2017; Vedapradha and Ravi, 2018; Ashta and Herrmann, 2021). On one side, technology drivers can improve products. The phenomenon of big data is one driver that enables a more extensive data pool for data analytics (Ashta and Herrmann, 2021; Cheng et al., 2021; Maiti et al., 2021; OECD, 2021; Deshpande, 2020). Another driver is faster computation, where the benefits are real-time aspects that come to favor (Shivkumar and Nihaal, 2017; Maiti et al., 2021; Milana and Ashta, 2021). Here, AI is valuable, for example, to measure and monitor market risks and volatility in financial markets (Giudici, 2018) and analyze a vast amount of data (Ashta and Herrmann, 2021; Shivkumar and Nihaal, 2017). However, a helpful prediction requires appropriate data analysis techniques (Ashta and Herrmann, 2021; Maiti et al., 2021; Vedapradha and Ravi, 2018). On the other side, there are economic reasons like lower costs (Bredt, 2019), eliminating human errors, and increasing scalability of business models or products to reach more customers and market segments (Shivkumar and Nihaal, 2017; Bredt, 2019). Second, AI research increases innovation and offers new options for business models, leading to rising profits (Bredt, 2019). Current examples of AI applications are financial management, financial markets, customer relationship banking, financial advisory, and financial technology (Adadi and Berrada, 2018; Ashta and Herrmann, 2021; Milana and Ashta, 2021; Shivkumar and Nihaal, 2017). An essential field in financial technologies' business models covers AI-supported risk management. For example, this pertains to various segments like underestimating creditworthiness (Donepudi, 2017), non-compliance with market risks, fraud detection, and cyber-attacks (Couchoro et al., 2021). Here AI can help support novel frameworks for risk management, considering new digital business models for financial technologies without stifling their economic potential (Giudici, 2018). In terms of innovation, the focus is mainly on the technological aspects that enable one to carry out existing tasks, such as checking for creditworthiness with the help of AI. However, from an innovation perspective, one might also discuss the novelty of connecting previously unrelated departments and job profiles with AI. Analyzing non-compliance with market risks, previously done by financial experts, is now done by a team of financial and AI experts. Thus, AI might lead to future synergies in leveraging cross-disciplinary innovations. Third, financial technologies may benefit from improving customers' financial services, e.g., monitoring account activity and analyzing and understanding customer activity. (Cao et al., 2020a; Deshpande, 2020; Shivkumar and Nihaal, 2017). AI has the potential to strengthen demand-led change in the business models of financial technologies. Data-driven analysis of historical customer data for personalized real-time adopted financial recommendations gets even more precise. This is fostered by more available data and the evolving AI capability to handle structured and unstructured data. (Ashta and Herrmann, 2021; PwC, 2020; Trocin et al., 2021. In addition, an advice gap can be filled by using AI to identify people who need financial help to prevent a personal crisis (The Finance Innovation Lab, 2018). In this context, peer-to-peer financial platforms are notably valuable for AI applications. Research sees potential in these platforms since they can be supplemented by AI-advisory, run at low transaction costs, and enable scaled credit lending, justification of creditworthiness, or crowdfunding (Ashta and Herrmann, 2021). Fourth, regulatory aspects, which are increasingly moving into the focus of supervisory authorities and financial institutions, are potential. Huge structural change in financial technologies is imminent to maintain competition, while, on the other hand, old regulations still apply to their day-to-day business (Paulet, 2018; Vedapradha and Ravi, 2018; Deshpande, 2020). Here, AI can support one side as a tool for financial technology-based applications used by authorities to get insights for regulatory, supervisory, and oversight purposes *("SupTech")* (Deshpande, 2020; OECD, 2021). On the other side, AI helps regulate institutions that are developing financial technology applications for stringent regulatory compliance requirements, reporting, internal controls, risk management, or misconduct prevention *("RegTech")* (Deshpande, 2020; Machkour and Abriane, 2020; OECD, 2021).

### 4.1.2 Technological potentials

Fifth, potential trends like deep learning, representation learning, or natural language processing are seen as innovation drivers and similar to chances from a technological view for financial technologies (Kute et al., 2021; Cheng et al., 2021). Chatbots or robo-advisors leveraging these technologies seem to stand out as a possibility, replacing and automating personal finance and wealth management more effectively than human advisors (Deshpande, 2020; Trelewicz, 2017; Shivkumar and Nihaal, 2017). Despite their potential, confidence in this form of AI has not yet reached the general population. Non-technology-savvy persons still tend to reject these applications. Furthermore, the widespread adoption of advanced AI applications in financial institutions still seems to be in its infancy (Vedapradha and Ravi, 2018). As another technological trend, algorithmic trading uses AI-based models to provide trading suggestions and power automated trading systems. Those make AI-based predictions, choose the course of action, and execute trades (OECD, 2021; Milana and Ashta, 2021). Additionally, decision support systems and AI enable analytical reasoning (Milana and Ashta, 2021). Furthermore, AI has reinforced existing financial technology applications. The interaction between AI and significant data phenomenon reinforces the informative value of financial technology applications, boosting the application's performance, facilitating more revenue, and enabling a better client approach (Vedapradha and Ravi, 2018; OECD, 2021). Thus, financial technologies invest in more extensive data collection capabilities (Ashta and Herrmann, 2021). This, for example, can be seen in the field of "smart" fraud detection, providing more accurate results (Shivkumar and Nihaal, 2017; Kute et al., 2021; Cheng et al., 2021). Systems referring to regulations, laws, and procedures can detect potential malpractice or anomalies at real-time speed and reduce costs (Ashta and Herrmann, 2021; Shivkumar and Nihaal, 2017; PwC, 2020; Donepudi, 2017). There are various subfields of fraud detection, like anti-money laundering (Giudici, 2018), illegal crypto markets (Giudici, 2018), and others (Pourhabibi et al., 2020).

### 4.1.3 Societal potentials

AI has benefits for society and employees as well. With the help of AI, the financial system might act more responsible, democratic, and fair without any human bias (The Finance Innovation Lab, 2018). Further, AI could help to avoid monotonous tasks and lead to a self-determined, responsible field of work (Deshpande, 2020). To achieve a justifiable level of fairness and enable innovative work with AI applications, these need concepts of responsibility for the systematic implementation of AI in real organizations, with fairness, explainability, and accountability at their core (Milana and Ashta, 2021).

## 4.2 Challenges using AI in financial technologies

Besides potentials, we revealed challenges in leveraging AI in financial technologies (see Table 4).

<table>
<tr><th></th><th></th><th>Internal reference</th><th>External/customer reference</th></tr>
<tr><td rowspan="9">Challenges</td><td rowspan="3">Economic & entrepreneurial</td><td colspan="2">Digital transformation</td></tr>
<tr><td>Internal structural adaptation</td><td></td></tr>
<tr><td colspan="2">Regulatory aspects</td></tr>
<tr><td rowspan="4">Technological</td><td colspan="2">Data privacy and confidentiality</td></tr>
<tr><td colspan="2">Data quality</td></tr>
<tr><td colspan="2">Data security</td></tr>
<tr><td colspan="2">Explainability and transparency</td></tr>
<tr><td rowspan="2">Societal</td><td></td><td>Change of work</td></tr>
<tr><td></td><td>Discrimination and injustice</td></tr>
</table>

*Table 4. Challenges for AI in financial technologies*

### 4.2.1 Economic & entrepreneurial challenges

The first challenge for many traditional financial institutions is digital transformation. Along the many economic or technological potentials previously described, financial technologies underlie innovation pressure since leveraging AI is only possible if the preconditions are set (Cao et al., 2020a). Financial technologies are increasingly trying to develop digital services leading to digital business models, which are enabled by trends like AI, blockchain, or cryptocurrencies (Milana and Ashta, 2021; Cao et al., 2020a). Hence, financial technology must undergo many steps to transform into a fully digital "neobank", where drawbacks like a dab IT infrastructure, less regulation, potential security breaches, and technical errors could lead to severe consequences (Maiti et al., 2021). In addition, the increasing networking of financial technologies leads to systemic risks, which affect the whole value-adding network (Cheng et al., 2021; Ashta and Herrmann, 2021). Another aspect worth mentioning is resource management. Different ranges of financial services require an adequate allocation of resources. Therefore, financial technologies will need skilled professionals (Maiti et al., 2021). Financial technologies must rethink developing new resources-based models to unify available tangible and intangible resources. Integrating human forces with the ongoing development of advanced technology progress needs to be considered (Maiti et al., 2021). The second challenge is directly connected to the general challenge of digital transformation, the internal structural changes to top competitors, benefitting lower operating costs, and others. A shift towards a data-driven enterprise architecture seems inevitable. Therefore frontend-office (customer-facing), middle-office (data analytics, service support), and back-office (administration) business divisions need to set up adequate technological and structural changes, which in detail are discussed in the literature (Maiti et al., 2021). Third, AI supports regulatory aspects only if a trustworthy data pool is available. Without such data, regulatory supporting tools could destabilize the financial sector and increase systemic risks to regional and international economies (Deshpande, 2020). In addition to the need for regulation geared toward digital economies, the explicability of regulatory boundaries for financial technologies is essential because only then will financial technologies understand how their models are affected by systemic risks (Barredo Arrieta et al., 2020; Deshpande, 2020).

### 4.2.2 Technological challenges

Fourth, cyber security, hacking, and other operational risks witnessed across digital financial products/services directly affect data privacy and confidentiality. While the deployment of AI often does not open possibilities of new cyber breaches, it could exacerbate pre-existing ones (OECD, 2021). Upcoming security risks using AI themselves need to be watched (Cheng et al., 2021). Speaking about cyber security in financial technologies, their interaction inside business networks enables a permanent threat of financial fraud since non-traditional financial institutions without high-risk control mechanisms represent a weak point (Cheng et al., 2021). Various types of financial fraud on new advanced techniques and methods of acting camouflage, making their detection difficult (Cheng et al., 2021).

Regarding data quality as a fifth challenge, there are questions about who takes responsibility for "bad data" and resulting lousy output by an AI system (Ashta and Herrmann, 2021). Typical problems can occur due to inadequate data for predictions, possible data bias, or non-appropriate data security (Ashta and Herrmann, 2021; Cao et al., 2020a; Cheng et al., 2021).

Data security is another challenge regarding the data volume, ubiquity, and continuous data flow for personalized analytics. This includes misuse, bias, and unfair or discriminatory consumer results. When using AI capabilities with data, it is also challenging to structure and organize the "noise" of the input data (Shivkumar and Nihaal, 2017). Knowledge extraction is another ever-discussed challenge in data science and the finance sector. AI systems must function robustly, securely, and safely throughout their life cycles. Potential risks should be continually managed, which involves training, validating, and testing their performance (Adadi and Berrada, 2018). However, AI's problem is not unique; it could amplify such vulnerabilities (OECD, 2021; Deshpande, 2020).

Because it is often hard to explain how AI-based knowledge extraction works in detail, the call for explainability for AI systems represents another challenge (Adadi and Berrada, 2018). Significant risks stem from the difficulty in understanding how AI-based models generate results (OECD, 2021), where the terms "*explainability*" and "*black-box*" refer to the difficulty in justifying or rationalizing model decisions or outputs (Hadji Misheva et al., 2021; Couchoro et al., 2021; Adadi and Berrada, 2018). The lack of explainability in AI models is one of the most widely acknowledged challenges, given the nature of these models (OECD, 2021; Hadji Misheva et al., 2021). Firms arguing against explainability with intellectual property rights could reinforce this lack (OECD, 2021; Hadji Misheva et al., 2021). However, with missing explainability, a lack of trust by users or an incompatibility with existing regulations could evolve if not adequately supervised by prudential authorities (OECD, 2021). There are already promising approaches that need to be expanded and tested, e.g., the LIME framework or SHAP values (Hadji Misheva et al., 2021).

### 4.2.3 Societal challenges

A major ethical issue is the impact of AI on society. Some voices fear a loss of jobs in the long term due to greater use of AI in the financial sector or predict a significant structural change in the world of work (Deshpande, 2020; Milana and Ashta, 2021). In the long run, every job-generating data could be fascinating to be automated by an AI agent (Deshpande, 2020). On the same page, the critical capabilities of employees will change since they need to increase their skills and knowledge in operating with data-driven AI applications (Deshpande, 2020; Cao et al., 2020a). The traditional task of "service providing" attributed to human employees seems to be increasingly replaced by robotic services (Belanche et al., 2019). The benefits of AI do not justify an operation at will without taking responsibility and guaranteeing a trustful AI deployment. AI should not be used as a substitution for independent human assessments (Ashta and Herrmann, 2021). In another literature review, the challenging aspects of responsibility and financial ethics have been detected, too (Suryono et al., 2020).

Another challenge impacting the working environment could be global incidents like conflicts between nations. Also, the amount of data, information, and technology worldwide is a credible challenge (Spence, 2021). Policymakers are sooner or later forced to make justifiable international regulations for AI applications, which could cripple our market system if not appropriately watched (Spence, 2021). Ultimately, AI can help avoid discrimination based on human interactions. Further, it can intensify biases, unfair treatment, and discrimination in financial services. These find their origin in existing biases dragged in from historical data of the natural world (OECD, 2021). AI could perpetuate injustices and inequalities by reproducing them in digital algorithmic decisions (The Finance Innovation Lab, 2018). Here, the approach of XAI might help to create transparency and trust, to notice imported data biases from the real world (Adadi and Berrada, 2018).

## 4.3 Requirements for the informed use of AI in financial technologies

Based on our findings in the literature, we derive requirements for the informed use of AI in financial technologies. Literature and policy already suggest the first requirements. A practical approach, mostly in line with the literature, is the EU legislation (European Commission. Directorate General for Communications Networks, Content and Technology. and High-Level Expert Group on Artificial Intelligence., 2019). They highlighted challenges from the technological dimension, such as data privacy, derive requirements such as privacy and data governance, and technical robustness and safety to be met. The societal challenges then allow deriving human agency and oversight requirements, accountability, societal and environmental well-being, diversity, non-discrimination and fairness, and transparency as crucial.

As a result, the requirements of human agency, transparency, and accountability are crucial for AI. These imply, in short, that: (1) Decisions must be informed, and there must be human oversight in the decision-making process, (2) the explanations must be pretty explained to the actors involved, and it should be evident that they are interacting with an AI, (3) mechanisms are defined that ensure accountability, verifiability, and evaluation of algorithms, data, and design processes.

EU regulations and literature (e.g., Arya et al. (2019)) also mention that different stakeholders and roles have additional requirements for AI. For example, a distinction is made between developers, operators, and end-users. Developers must implement and apply the criteria while the operators ensure that the AI meets the required specifications. End users are to be informed about the needs and demand compliance. On the one hand, it is striking that most of the literature (e.g., Adadi and Berrada (2018; Bussmann et al. (2020); Barredo Arrieta et al. (2020)) constantly argues about ethics.

On the other hand, the literature (e.g., Liu et al. (2021), Suryono et al. (2020), and Barredo Arrieta et al. (2020)) is partially consistent with the previously mentioned requirements. However, from our derivation of the requirements from the challenges, it is evident that the EU guidelines entirely disregard the economic aspect and technical depth. Furthermore, we can infer that it is necessary to make AI trustworthy so people can rely on AI-produced results without worrying about potential harm (Liu et al., 2021). Therefore, trust is an essential requirement to fully realize the potential of AI so that people can fully leverage the benefits and conveniences of advanced AI.

## 4.4 Leveraging the full potential of AI with XAI

AI applications are becoming increasingly unavoidable as users want to understand, appropriately trust, and effectively manage the results of AI (Adadi and Berrada, 2018). Based on illuminating the potentials and challenges of AI, our findings show that complex AI containing black boxes needs to be extended with components for explainability. This would reduce the challenges addressed above. Based on the literature, the explicit call for removing the black box stems from the following reasons.

First, restrictions still occur to successfully leverage the new promising business areas, where AI should become explainable. This is caused by the responsibility of the numerous fields of applications, where financial technologies today already successfully leverage AI (Ashta and Herrmann, 2021; Milana and Ashta, 2021; Barredo Arrieta et al., 2020). Second, XAI helps facilitate regulatory processes. The literature calls for laws and regulations to be updated and effectively adapted to the digital world, as technologies like AI impact today's business models and continuously evolve (Machkour and Abriane, 2020; Deshpande, 2020; Barredo Arrieta et al., 2020). Besides, XAI needs to be accordingly integrated into the requirements of the highly regulated financial sector to provide fair decisions and justifications for loaners and authorities, including security, human rights, and other aspects, where AI will be a crucial trend for regulation (Adadi and Berrada, 2018; Stahl, 2022). Additionally, with a vast amount of unstructured information historically reviewed manually, regulatory tasks can now easily be automated with intelligent AI-based applications (Shivkumar and Nihaal, 2017). Third, XAI is critical to enabling transparency in data analytics. When AI processes are transparent to user problems, data bias, discrimination, or false implications can be more accurately identified. In addition, data quality can be better assessed when the AI output is explainable. Fourth, explainability is essential for customers to justify generated financial advice (Adadi and Berrada, 2018). Therefore, XAI could lead to more valuable, intelligent, personalized recommendations for customers in "smart customer services", which already belong to the most preferred investment areas in the financial sector (Cheng et al., 2021). AI applications must be continuously improved and trained to deliver the most accurate results possible. Identifying factors that strongly influence decision-making, complex, explainable, and interpretable AI enables the entire decision-making process to improve performance, compliance, and accuracy of predictions in continuous iterations. Addressing societal concerns, XAI could change the role of AI in society to one of hope as a sign of a self-fulfilling way of working (Deshpande, 2020; Barredo Arrieta et al., 2020; Maiti et al., 2021). It is also significant to use XAI to prevent erroneous behavior. If developers know more about an AI system's decision behavior, they may better detect and avoid potential errors and vulnerabilities. XAI would thus contribute to better control of decision-making. It should be noted that developing and leveraging XAI systems provides several benefits. First, it ensures impartiality in decision making; second, it provides robustness by highlighting potential adversarial perturbations; third, it ensures that only meaningful variables derive output to ensure truthful causality within the reasoning model. (Adadi and Berrada, 2018).

Generally, financial technologies should be open for the use and development of XAI. They should not ban the request for transparency from the outset. Recognized state-of-the-art approaches in granting explainability, e.g., the LIME framework or SHAP values, in AI systems that already exist but do not find enough use in application yet (Hadji Misheva et al., 2021). XAI provides the necessary information to justify decisions, thereby verifying the black-box decisions made and labeling them as ethical, which helps build a relationship of trust.

### 4.5 Challenges when implementing XAI

While XAI offers several advantages, challenges stay partly. The desire for increasing explainability could lead to a system acting less performantly and efficiently (Adadi and Berrada, 2018). As literature confirms (Adadi and Berrada, 2018), making a complex AI explainable is undoubtedly very expensive, as significant human and computational resources would have to be devoted to its development. Thus, each case has to be leveraged why and when XAI is useful. The use of XAI depends fundamentally on the degree of opacity caused by the black box and how error-resistant the specific application area is (Adadi and Berrada, 2018). In addition, it must be considered how the costs can be reconciled with the requirements or the need for explainability, for example, by legal framework conditions. Due to the nature of the highly regulated financial technology environment, legal requirements must be met, and not every organization has the resources to meet these requirements. Furthermore, the aspect of security must be considered. Since AI and XAI function in a data-driven manner, they are inherently vulnerable to manipulation. It is conceivable that negative examples could be generated to deceive the classifiers of the AI itself and its explainability component. XAI does not influence the performance and which data is used, according to the “garbage-in-garbage-out” principle (Ashta and Herrmann, 2021). This shows that human interaction in XAI is still significant. As already mentioned in the requirements, a human-in-the-loop supervisor must ultimately check whether the results are accurate, correct, and justifiable at the current stage of development. An often-mentioned challenge regarding XAI is defining what constitutes a sufficiently good explanation (Wenninger et al., 2022). Therefore, the qualitative and quantitative assessment of interpretability should be further investigated (Liu et al., 2021). This challenge stems from recognizing that different groups and stakeholders require different explanations. It must be clarified in what form and to what extent an output must be explained so that the intended target group sufficiently understands it. This also requires the development of a method to make explainability comparable and measurable. However, this conflicts with the fact that the explainability of an AI is highly use case dependent and cannot simply be transferred to other use cases and industries. It must be clarified in which form and to what extent an output must be explained so that the intended target group sufficiently understands them.

## 5 Discussion

We addressed the research question of how XAI can contribute to leveraging AI in financial technologies. Conducting a structured literature review, we identified and systemized the potentials and challenges of AI in financial technologies before deriving requirements for the informed use of AI and subsequently mapping them with the potentials of XAI. We structured the potentials and challenges of AI in economic, technological, and societal dimensions alongside their mapping to financial technology internal and external (i.e., customers) references. We find that the EU already proposes relevant requirements for the informed use of AI but lacks economic and technical aspects crucial for practice. Central, XAI allows tackling AI’s black-box nature and ensures the interpretability of AI’s decisions.

Our results have several implications for practice, policy, and research. First, financial technologies should start to deal with XAI, as it is directly linked with economic, technological, and societal benefits and challenges that can reduce the limitations of AI, as found in the literature. This will help establish a general understanding of AI's capabilities and limitations. At the same time, this fosters the acceptance of XAI while reducing concerns caused by inexperience. Second, XAI will not solve all AI problems and challenges in practice. Instead, XAI is a promising approach to solving some of today's challenges but must be viewed as case-dependent, as evident in literature across different application domains. Further, the measures of explainability should be clearly defined for legal reasons to ensure a consistent understanding and targeted use of XAI. Literature highlights that objective measures of a reasonable explanation differ between individuals and use cases. Therefore, we propose that explainability should measurability be defined depending on the use case, stakeholders, and the goal pursued with XAI. Only in this way the full potential of XAI can be leveraged, and transparency ensured. Fourth, when applying XAI, a trade-off between prediction performance in terms of accuracy, computational effort, and explainability and the consideration of classical challenges of AI should be considered. Mainly for practical applications, the additional computational time required by XAI might lead to limitations in usage. Classic challenges of AI, such as concept drifts or security, must still be considered when using XAI the same way as in other AI projects. Research efforts could draw on this and support the dissemination of XAI in practice by developing less computationally intensive and efficient approaches. Fifth, policymakers should intensify their efforts to provide guidelines and frameworks for XAI to enable the trustful use of AI, especially for critical applications in financial technologies. This is the only way to ensure an overarching framework and avoid neglecting relevant aspects, despite the unique ways XAI can be developed. However, this implication might contradict XAI's subjective interpretation and the introduction of guidelines and frameworks for XAI. To resolve or address this apparent contradiction, it is vital to define and understand at what level policymakers should start. If one considers guidelines and frameworks at a very detailed level, i.e., at a use case level, then precisely the contradiction of overarching guidelines and subjective interpretation will hold. In contrast, the contradictions may diminish if one evaluates XAI from a higher level. On such a level, general guidelines, such as providing information on the nature of AI and XAI and how they are addressed/reflected in related services and products to ensure transparency and provide customers with a sound basis for decision-making, may be considered when developing guidelines and frameworks. It must therefore be ensured that the framework for dealing with AI and XAI in a trustworthy manner is created, but that the exact implementation, also to allow for future (technological) developments, is not restrictive. Research can provide support through appropriate definitions and the possibilities for measurability approaches to explainability, and organizations from the field can bring experiences and challenges to the attention of political bodies and decision-makers. The EU guidelines already mentioned above are a suitable option for further intensification.

Naturally, our work has some limitations but equally provides opportunities for further research. First, our research is limited in data and methodology with a fixed search string, selected databases, and whitepapers from the industry. As a relatively new research field, the available literature is limited in quantity and time, as most articles were published in 2020 and 2021. Thus, our work is a first attempt that encourages further updates based on a broader literature base in the coming years. Additionally, researchers might extract information from industries already successfully applying XAI in practice to complete the picture – e.g., by interview studies. Second, we have focused our work on literature. Expanding this focus to include insights from the field, e.g., expert interviews, could further broaden our findings' scope and practical applicability. Third, our results could differ geographically, as the level of digitization, regulatory requirements, and economic strength or weakness could vary across regions. Researchers might investigate such aspects in an international research consortium. Fourth, we did not focus on technical aspects and solutions, which might cause a restricted view of the topic. Future research might map our insights on the potentials and challenges of XAI with tangible technical approaches to support XAI implementation in practice. Nevertheless, we are convinced that our work will help researchers and practitioners with a structured overview of XAI in financial technologies.

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