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Artificial intelligence in EU securities markets

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Financial innovation

Artificial intelligence in EU securities markets

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Summary

The use of artificial intelligence (AI) in finance is under increasing scrutiny from regulators and supervisors interested in examining its development and the related potential risks. This article contributes by providing an overview of AI use cases across securities markets in the EU and assessing the degree of adoption of AI-based tools. In asset management, an increasing number of managers leverage AI in investment strategies, risk management and compliance. However, only a few of them have developed a fully AI-based investment process and publicly promote the use of AI. In trading, AI models allow traders, brokers, and financial institutions to optimise trade execution and post-trade processes, reducing the market impact of large orders and minimising settlement failures. In other parts of the market, some credit rating agencies, proxy advisory firms and other financial market participants also use AI tools, mostly to enhance information sourcing and data analysis. Overall, although AI is increasingly adopted to support and optimise certain activities, this does not seem to be leading to a fast and disruptive overhaul of business processes. A widespread use of AI comes with risks. In particular, increased uptake may lead to the concentration of systems and models among a few 'big players'. These circumstances warrant further attention and monitoring to continue ensuring that AI developments and the related potential risks are well understood and taken into account.

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Introduction

The availability of increasing volumes of data from different sources, coupled with the continuous growth of computing power, provides the ideal conditions to foster advancements in the use of artificial intelligence (AI) – and, more specifically, of machine learning (ML) – across the financial sector, including securities markets. By harnessing data via advanced statistical techniques and computer science, AI and ML have the potential to be transformative technologies. Accordingly, in recent years, policymakers, regulators and supervisors around the globe have devoted attention to how AI techniques are applied in the financial services sector to understand the related implications and to assess potential risks. At the same time, detailed evidence on recent developments as regards the use of AI in European financial markets is scarce.

Based on information collected via data providers, surveys, and market intelligence, this article explores common applications of AI currently used by entities that operate in different sectors of EU securities markets. It assesses the prospects for increasing uptake of AI in these areas, with the associated risks and challenges.

Promoting the uptake of AI tools in the financial sector while ensuring that they are used in a responsible way is a priority of the Digital Finance Strategy adopted by the European Commission in September 2020 (European Commission, 2020). The Commission also notes that the ongoing digital innovation in the financial sector entails a number of risks that are either inherent to new technologies or amplified by them. Monitoring related developments is thus critical to safeguarding consumer protection and financial stability while supporting an orderly digital transformation. By providing a better view of the state of the market, this article aims to inform regulatory and supervisory prioritisation in this sphere.

AI does not have a standard, universally shared definition. Rather, it is used as an umbrella term to designate a broad set of methods that enable problem-solving via a combination of statistics and computer science.[2] In this sense, a large part of what is branded as AI in finance is not technically new but has existed in the form of statistical or econometric modelling techniques for a long time. Continual growth in computing power and data has enabled existing techniques to be applied to a range of problems on a large scale.

Accordingly, many of the issues associated with financial institutions' use of AI are quite similar to those posed by traditional models.[3] However, the scale at which AI can be used, the speed at which AI systems operate, and the complexity of the underlying models may pose challenges to the market participants intending to use them and to their supervisors. As a consequence, most regulators are in the early stages of developing AI-specific governance principles or guidance for financial firms.[4] In one of the major international efforts in this regard, the Commission presented its AI package in April 2021, including a proposal for a regulation laying down harmonised rules on AI (the 'AI Act') and a related impact assessment (European Commission, 2021).[5] The AI Act is a

[2] In fact, different – but substantially compatible – definitions of AI have been developed recently. European Commission (2021) defines AI as software that "can generate outputs such as content, predictions, recommendations, or decisions influencing the environments they interact with" and which is developed with one of a number of techniques, including ML, logic- and knowledge-based approaches, and statistical approaches. European Council (2022) adopts a similar definition while further specifying that an AI system "is designed to operate with elements of autonomy" and "infers how to achieve a given set of objectives". IOSCO (2021) defines AI as "the science and engineering of making intelligent machines, or simply, the study of methods for making computers mimic human decisions to solve problems". OECD (2021) defines AI as "machine-based systems with varying levels of autonomy that can, for a given set of human-defined objectives, make predictions, recommendations or decisions". FSB (2017) defines it as "the theory and development of computer systems able to perform tasks that traditionally have required human intelligence".

[3] See Prenio and Yong (2021), p. 20. An exception identified by the authors is issues related to AI's 'fairness'.

[4] In 2021, EIOPA published a report on AI governance principles (EIOPA, 2021) and the EBA published a discussion paper on ML for IRB models (EBA, 2021). The European Supervisory Authorities (ESAs) have engaged with stakeholders on the impact of potential developments in AI since 2018; see the *Joint Committee Final Report on Big Data* (Joint Committee of the European Supervisory Authorities, 2018). For thorough reviews of the different approaches and initiatives that regulators have taken worldwide, see Prenio and Yong (2021) and IOSCO (2021).

[5] Besides the AI Act, the AI package included a *Communication on Fostering a European approach to artificial intelligence* and a review of the Coordinated Plan on Artificial Intelligence (see European Commission, 2021).

cross-sectoral legislative proposal with the objective of ensuring the trustworthiness of AI following a risk-based approach: for riskier AI applications, stricter rules apply.[6] An aim of the present article is to facilitate an understanding of the interplay between industry practices and the regulatory framework.

The remainder of the article is organised as follows. The next section explores how various institutions are leveraging AI tools in the context of asset management. We then present findings on how AI is used over the life cycle of trading, starting with pre-trade analysis, through the execution phase, and on to post-trade processes. The subsequent section provides insights into tools used by credit rating agencies and proxy advisory firms. Then, we explore potential risks associated with the uptake of AI in securities markets. In the last section, we provide some concluding observations and discuss implications.

TEXTBOX 1

Main artificial intelligence concepts

Machine learning (ML). ML can be defined as systems that can learn and adapt without following explicit instructions, using algorithms and statistical models to analyse and draw inferences from patterns in data. It is commonly understood to be a subset of AI.

Natural language processing (NLP). NLP refers to the branch of AI concerned with processing text and spoken words and understanding their meaning. Combining computational linguistics with statistical and ML methods, it entails vectorising words, sentences, or longer text so that they can be fed into a statistical model. It may or may not be based on ML.

Supervised learning. Supervised learning refers to ML models that are trained on labelled data. The model 'learns' from both previous input data and the previous results (which represent the labels), and is later used to predict an outcome based on new, unlabelled input data.

Unsupervised learning. Unsupervised learning refers to ML models that, unlike supervised learning, are trained only on unlabelled inputs. Algorithms then form clusters based on similar properties. It is known as unsupervised learning because the algorithms classify the data without prior human intervention to label the training data.

Reinforcement learning. Reinforcement learning is a type of ML that does not require a labelled dataset as supervised learning does. Nor does it use an unlabelled dataset in the same way as unsupervised learning does. Rather than seeking to discover a relationship in a dataset, the purpose of reinforcement learning is for the model to learn an optimal policy that maximises the 'reward function' or another user-provided reinforcement signal that accumulates from immediate rewards.

Deep learning. Deep learning is an ML method based on neural networks (see Textbox 3) composed of multiple layers. The number of parameters makes this method extremely flexible and apt for many tasks. It can quickly learn from its errors and thereby improve its accuracy. However, this comes at the expense of limited stability of the output under variations in the sample data and little to no explainability. Moreover, the many parameters require a large amount of data for the model to be trained. Deep learning can be applied to supervised, unsupervised or reinforcement learning tasks.

Parametric versus nonparametric models. Parametric models refer to functional forms that have a finite number of parameters. The underlying probability distribution is assumed to be completely determined by the knowledge of the parameter set. When the functional forms of the distributions are unknown, the model is denoted as nonparametric. Nonparametric models generally need a larger amount of data to produce accurate predictions.

Asset management

Portfolio management: growing interest

Portfolio managers are making use of a variety of tools that can be classified under the umbrella of AI. AI techniques can be used by discretionary portfolio managers to enhance fundamental analysis and by quantitative funds as part of

[6] The Act categorises the risks of specific uses of AI into four different levels: unacceptable risk, high risk, limited risk, and minimal risk. In its preliminary assessment, the Act identified no high-risk use case related to securities markets.

systematic investment strategies (e.g. to optimise portfolio construction by estimating the structure of dependence among financial assets). How these techniques are integrated into the investment process – and how far AI can inform the associated investment decisions – varies significantly.

AI appears to be used mostly as a tool to execute specific tasks that leverage large amounts of data. In fact, the ability to extract information efficiently from a wide range of large numerical and textual datasets with minimal human supervision is driving AI adoption – in at least some form – by an increasing number of funds.[7]

A distinctive trait of AI – as opposed to more traditional methods for technical or fundamental analysis – is the increasing inclusion of alternative and unstructured datasets among the information sources relevant to the identification of investment opportunities.[8] In this context, natural language processing (NLP) techniques, which extract economically meaningful information from various sources of text, appear to be particularly popular among AI adopters. NLP is commonly used to identify salient news items and to develop sentiment indicators. An application that industry experts often mention is the identification and assessment of environmental, social and governance (ESG) disclosures. Market intelligence suggests that investment professionals use NLP to generate real-time ESG assessments based on firms' communications such as corporate social responsibility reports. Some portfolio construction specialists are marketing solutions that cater to institutional investors' emerging ESG-related business requirements.[9]

Based on industry practitioners' feedback, AI does not seem to be transforming portfolio managers' investment practices in a disruptive or revolutionary fashion. Few funds are known to have developed a fully end-to-end AI-based investment process. According to several industry experts, asset managers using advanced AI strategies are typically specialist hedge funds that are run by analysts with strong ML backgrounds and that bet on AI as a marketing proposition.[10]

It is difficult to assess whether a specific technique prevails when AI (and specifically ML) is used in systematic investing. Neural networks (see Textbox 3) are presumably a popular approach, as these models have been found to perform best, although 'ensemble' approaches that combine a number of different ML techniques have been shown to produce better predictions than any individual ML technique (see, for example, Borghi and De Rossi, 2020).

Overall, integrating ML into the investment process should not be seen as an obvious, automatic way to improve fund performance. As argued by CFA Institute (2021), hiring specialists with specific technical expertise appears critical for an ML-based investment approach to deliver significant results.

Data is also crucial to the successful use of AI. Academics and industry experts often mention that financial data time series are short relative to

[7] It is hard to quantify precisely what proportion of asset managers use AI. Recent investigations found that natural language text understanding is adopted by 32% of respondents across the entire financial services industry (Zhang et al., 2022, p. 162), whereas 22% of EMEA finance professionals use big data analysis and ML techniques "to conduct market research that leads to investment decisions" (CFA Institute, 2020). In a worldwide survey conducted in March 2019 (CFA Institute, 2019), 31% of portfolio managers reported using at least one of the 10 listed AI techniques for creating trading algorithms, and 10% stated using AI/ML techniques in the investment strategy "to find a nonlinear relationship or estimate" (a narrower interpretation likely to apply mainly to systematic strategies). These figures are likely to be an underestimate for technologically savvy entities such as quantitative investment funds. CFA Institute (2019) argues that unstructured and alternative data is also used by discretionary managers who perform fundamental analysis. In a separate sample of equity and credit analysts, 25% reported using AI or ML for industry and company analysis, whereas 56% used unstructured and/or alternative data. Elsewhere, Linciano et al. (2022) found that, out of eight asset management companies covering 60% of the Italian market, seven are using AI systems in some parts of their business, and three have fully implemented AI systems to optimise the investment process. It should be noted that, as highlighted in FSB (2017) and OECD (2021), there is not always a common definition or understanding of what is included within the concept of an AI system, and firms are usually hesitant to share detailed information on their investment process.

[8] Alternative data is characterised by the fact that it is primary information: information that cannot be obtained from any other source at that given time. That is why this data (such as public speeches, social media content, and satellite imagery) is typically unstructured (i.e. it has not been previously collected and processed by data providers to convert it into a traditional 'structured' format, such as a numeric matrix).

[9] As an example, a technology company offers an AI-based platform to "build alpha-generating investment strategies that are hyper-customised for clients' sustainability objectives".

[10] In the United States, the Eurekahedge AI Hedge Fund Index, designed to provide a measure of the performance of underlying hedge fund managers who utilise AI and ML in their trading processes, had 12 members as of October 2022 (see www.eurekahedge.com/Indices/IndexView/Eurekahedge/683/Eurekahedge-AI-Hedge-fund-Index).

cross sections or, in the case of high-frequency data, are characterised by a low signal-to-noise ratio. These characteristics make them different from the data typically used in successful ML applications outside finance. Structural breaks in time series or 'regime shifts' may also limit the appropriateness of this data to make economic forecasts, which renders many of the AI models currently in use better suited for short-term frameworks rather than long-term decision-making. Notwithstanding these challenges, research is ongoing at some firms at the cutting edge of the use of AI in the investment process, aiming to develop ML models that take into account changes in financial markets' regimes.

Besides supporting fundamental and technical analysis, AI can be the backbone of portfolio risk management models. Some hedge funds and asset managers are automating risk management and compliance processes by tracking the behaviour of individual portfolio managers, automating the execution of quality reports, and assessing market liquidity risk (see IOSCO, 2021). AI techniques can also be used in early warning systems to predict market volatility and financial crises (see Bartram et al., 2020).

Investment funds: hesitant to publicise AI use

Although interest in using innovative AI tools is growing among even traditional investment funds, their actual use appears to be still constrained by not only technological and knowledge barriers – especially amongst smaller asset managers – but also mixed feedback from clients. In a sector where AI still lacks widespread acceptance, the perceived risks of black boxes and the challenge of explaining negative outcomes may deter certain investors.

To shed further light on this aspect, we collected data to assess how many funds decided to disclose to investors that they leverage AI or ML tools. We did this by analysing the universe of open-end investment funds covered by two financial data providers. Specifically, we used text-mining methods to screen approximately 145,000 financial documents issued by investment funds domiciled in the EU (including prospectuses, key investor information documents (KIIDs), shareholder reports, factsheets, etc.), covering a minimum of 22,000 funds.[11] Then, we inspected all documents in which the phrases "artificial intelligence" or "machine learning" occurred, and identified those funds that mentioned using AI or ML as part of the investment process.[12] To complement this search, we inspected all funds recorded in either the Morningstar Direct database or the Refinitiv Lipper database whose names contain the term "artificial intelligence" or "machine learning", or their abbreviations, and – for funds not already in our sample – similarly identified those entities that stated that AI or ML underpin their investment process (as opposed to, for example, funds that invest predominantly in companies developing AI technologies).

The results of this exercise indicated that most investment funds do not explicitly advertise the use of AI: in total, we found 65 funds – offered by 40 different fund management companies – that indicated leveraging AI (or, more specifically, ML) in their investment strategies. Fifty-six of these offer share classes open to retail investors. Chart 1 shows how many of these funds have been on the market and their assets under management over the past five years.

Over this period, the number of existing funds has increased five-fold to reach 54 entities as of 3Q22, of which 29 were equity funds, 13 invested in alternative assets, 10 invested in mixed assets, one invested in bonds, and one invested in real estate. In addition, 11 funds have already been liquidated. This multiplication of funds disclosing the use of AI notwithstanding, their footprint in the market remains very limited in relative terms: they constitute less than 0.2% of the number of undertakings for collective investment in transferable securities (UCITS) funds in the EU,

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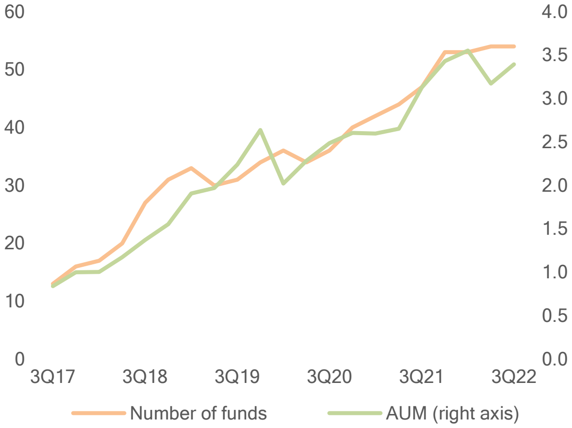
11 We screened all of the documents available on all existing Morningstar webpages of EU-domiciled mutual funds. Given that the documents retrieved usually contained information on multiple funds, some of which have not been recorded by Morningstar, the figure of 22,000 funds is likely to be an underestimate of the total number of funds for which documents have been screened. Sample collection started in mid-2020 and was updated yearly. The sample includes all documents available at any of these collection dates, regardless of the publication date. However, we cannot rule out the possibility that some documents or fund webpages that were available before 2020 have been subsequently removed by Morningstar.

12 This process led to the manual review of over 1,000 documents. We identified funds that use AI or ML as the sole investment strategy and funds that state that AI or ML support one of a range of available investment strategies. The extent to which an AI or ML model determines the investment decision and the degree of human judgment involved also vary on a case-by-case basis. The terms were not translated into languages other than English.

and around 0.03% of UCITS' assets under management.[13]

Chart 1
Investment funds that declare using AI or ML
Funds publicising AI use increasing but limited

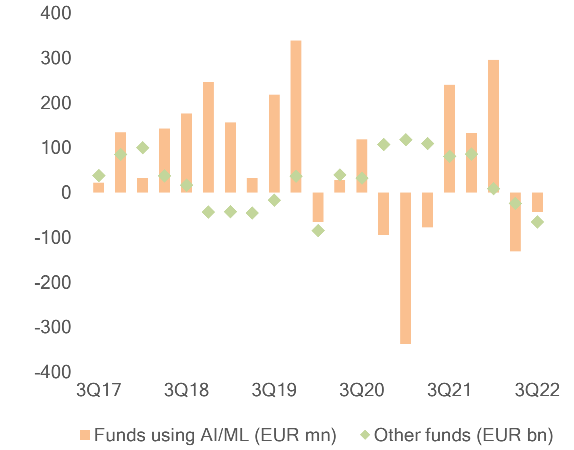


Note: The chart displays the number (left axis) and assets under management (right axis, in EUR bn) of EU investment funds that declare using AI or ML as part of the investment process in publicly available documents such as prospectuses, KIIDs, and shareholder reports. Information on assets under management was not available for 14 funds.
Sources: Morningstar Direct, Refinitiv Lipper, ESMA

Chart 2 further shows that funds using AI have obtained mixed success among investors, having experienced net outflows over five of the last eight quarters. In comparison, investor flows at other EU investment funds were negative only in the two latest periods.[14] In further analysis, we similarly identified all funds that mention NLP, and found only nine additional entities that reported using related methods within the investment process.[15]

All in all, these figures appear low, especially considering that the meaning of AI can be broad and there is no binding definition that could discourage fund management companies from advertising its use (for example to avoid the risk of making false claims and attracting regulatory oversight). The choice to avoid references to AI may be explained by the fact that – as reported in the previous subsection – many funds use AI to carry out limited steps of the decision-making process with no immediate effect on the investment strategy and investment policy, which are usually the focus of investor disclosure documents. At the same time, some companies' discretion is likely to be rooted in the market environment they face. In line with anecdotal evidence received from market participants that some investors may associate AI with a lack of transparency or accountability, investment firms may be mindful of reputational repercussions from explicitly promoting the use of AI.

Chart 2
Flows of investment funds that declare using AI or ML
Inflows uneven



Note: Bars represent investor flows (in EUR mn) for EU investment funds that declare using AI or ML as part of the investment process in publicly available documents such as prospectuses, KIIDs, and shareholder reports. Squares represent investor flows (in EUR bn) for a sample of between 22,564 (3Q17) and 22,941 (3Q22) EU investment funds investing in equity, mixed assets, and alternative assets.
Sources: Morningstar Direct, Refinitiv Lipper, ESMA

Hence, our figures may underestimate the number of funds that could reasonably claim that making use of some form of AI aids their decision-making processes. However, they are likely to capture most of those specialised funds that adopt a systematic investment approach rigorously entrusted to ML-based models. These funds are more likely to make this a key point of their marketing strategy. In fact, out of the 65 funds identified, 35 funds directly mention AI or ML in their names, thus making these concepts

13 At the end of 2021, the EU hosted approximately 29,100 UCITS funds with a total of EUR 11.4tn in assets under management. Equity funds were approximately 11,400 of these, with assets amounting to EUR 4.8tn (EFAMA, 2022). The figures on assets under management of funds that use AI or ML exclude 14 out of 65 funds for which this information was not available.

14 Notwithstanding this outcome, statistical tests did not show flows at these funds to be significantly different from flows at other comparable funds over the sample period.

15 We constructed a separate sample for funds mentioning the use of NLP, as we observed that this term can have a broad meaning among AI practitioners, involving anything from simple text mining to advanced ML models.

central to their selling proposition.[16] These vehicles may have been conceived by asset management companies with the objective of catering to a specific group of clients who have a favourable view of innovative and sophisticated investment tools.

To further assess the success of funds that use AI, we investigated whether these techniques allowed these funds to outperform their peers. Table 1 shows that average returns and alphas of funds using AI over the three years to October 2022 are not significantly different from those of funds that do not make any reference to the use of AI in their investment strategy. We also conducted further statistical tests that control for other characteristics in order to compare the performances of funds that use AI and funds that are otherwise similar. No statistically significant difference emerged between the two groups. Finally, we checked whether funds that use AI have higher or lower costs than their peers, and we similarly found no significant result in either direction (see Table 1).[17] Hence, we could not find evidence suggesting either that AI enables lower fees by containing costs or that it is exploited as a selling point to charge excessive fees to investors. This is in line with the seeming lack of a strong demand inherently tied to AI or any 'hype' around its use.[18]

In principle, the use of AI and ML in investment management provides the prospect of efficient investment decisions and the potential – if the technology is applied at a greater scale – to reduce fund operating expenses over time. However, based on our findings for those funds that explicitly promote it, the technology may not yet have consistently translated into superior outcomes for fund investors.

Table 1
Characteristics of funds that declare using AI or ML
Performance and costs not significantly different

	AI funds	Others	Difference (95% conf. interval)
Return (%)	0.30	0.26	[–0.24, 0.30]
Alpha (%)	0.17	0.23	[–0.32, 0.22]
TER (%)	1.33	1.43	[–0.30, 0.11]

Note: The table shows average performance and costs of EU investment funds that declare using AI or ML as part of the investment process (column "AI funds") and of other EU investment funds (column "Others"). The sample contains funds investing in equity, mixed assets, and alternative assets. The column "Difference" displays the 95% confidence interval for the difference between the values in the columns "AI funds" and "Others", based on a *t*-test for the equality of means. "TER" is the average total expense ratio (or per-annum ongoing costs) in October 2022 (for 40 AI funds and 19,985 others). "Return" and "Alpha" are average raw returns and alphas, net of costs, calculated monthly over 36 months from November 2019 to October 2022 (for 26 AI funds and 17,356 others). "Alpha" is calculated monthly with reference to a fund's technical indicator benchmark.
Sources: Morningstar Direct, Refinitiv Lipper, ESMA

Robo-advisors: currently limited gains

Robo-advisors are automated portfolio managers, that is, computer programs that produce optimal portfolios tailored to investors' risk appetites. Although they can be based on complex systems built around big data, which AI can potentially enhance, in practice most robo-advisors appear to be based on relatively simple algorithms that use limited information on the

[16] In addition, some fund names that do not include AI or ML include keywords clearly associated with quantitative investment, such as "quant", "numeric" or "smart alpha". Note that, whereas the names of all funds – over 80,000 – in the Morningstar Direct database and in the Refinitiv Lipper database were screened, related documents could not be retrieved and screened for all funds. Hence, our sample might not capture some funds that mentioned AI or ML in their investment strategy but not in their names. However, most of the funds for which documents were not available were liquidated in the past and are less likely to have mentioned using AI or ML in financial documents.

[17] Specifically, we estimated linear regression models of fund returns, alphas, and total expense ratios on a number of fund characteristics over the sample period, including whether the fund uses AI, or, in an alternative specification, has AI in its name. Control variables included fund size, age, fees, benchmark, and the proportion of share classes dedicated to institutional investors. Significance levels were obtained clustering standard errors at the fund level to account for autocorrelation in the dependent variables.

[18] In the United States, a number of active exchange-traded funds (ETFs) that claim to implement AI-driven strategies have been launched in recent years. Bartram et al. (2021) identified 13 active ETFs whose investment process is driven by AI/ML by performing a systematic search on all active ETFs traded in the US market, albeit their scope was limited to fund descriptions and the Reuters/Refinitiv newsfeed. These funds hold less than 1% of the total assets managed by active ETFs in equities, but have enjoyed significant growth. They charge fees that are slightly above the level typically charged by active ETFs, but do not significantly outperform them after accounting for the portfolio's exposure to a set of standard style factors. Previously, Rabener (2019) estimated that ETFs powered by AI had not reached a meaningful size as of the end of 2019, with total assets under management estimated to stand at approximately USD 100mn. More recently, Boyde (2021) identified six ETFs powered by AI from two management companies, with a total of USD 270mn in assets.

client – such as investment horizon and risk tolerance.[19]

Industry experts surveyed by ESMA highlighted that it is not clear whether making AI an integral part of robo-advisors – likely relying on more advanced underlying models and a larger volume of data – would be profitable or desirable.

There are reasons to be sceptical that AI could be decisive in this context. First, technical constraints may make it challenging to improve the performance of robo-advisors via AI. For example, collecting larger amounts of personal or alternative data, thereby increasing the tool's complexity and 'personalisation', is not guaranteed to improve outcomes based on classical portfolio theory.[20] This approach may also be at odds with the need to contain these services' costs and promote their scalability, elements that tend to be central to robo-advisors' business case, given the narrow margins they typically grant.

Furthermore, a more complex framework may make retail investors wary of robo-advisors, given that explainability has been found to be a critical factor affecting consumers' trust in automated platforms (Bianchi and Briere, 2021).

Another limiting factor could be the interplay with existing regulatory requirements, such as the GDPR's right to explanation, which empowers users to inquire about the logic involved in an algorithmic decision affecting them.[21] Despite the unclear outlook, some academics do suggest that robo-advisors may be increasingly moving towards the use of predictive ML algorithms.[22]

AI service providers: trend towards outsourcing?

A notable trend in the European asset management industry is the emergence of AI-native tech firms that provide services to institutional investors in one or more fields, including portfolio management, risk management and compliance. AI-based compliance tools include tools for data anomaly detection, automated reporting, and automated generation of legal documents such as fund prospectuses, PRIIPs KIDs, and the European ESG Template. These use cases are examples of the transformative potential of RegTech, i.e. the use of technology to enhance regulatory and compliance processes.[23]

In the domain of compliance, one firm identified the regulatory roadmap as the main factor determining the demand for their services, but also observed an autonomous drive to digitalisation and business transformation. Moreover, ESG-related data is often the focus of tools aiming to provide information and signals for clients to use as input for quantitative or discretionary investment strategies. The services are often provided via cloud-based platforms.

Interestingly, these firms seem to make the use of AI the selling proposition of their business. Although it is difficult to estimate these companies' success and market share, this strategy contrasts with the relatively limited recourse to AI as a branding tool among investment funds.

Most of the surveyed firms stated that they offer customised solutions, allowing varying degrees of autonomy to clients. For instance, the data used is either provided by the clients or collected in-house, depending on the use case and the

[19] An analysis of 219 international robo-advisors shows that Markowitz's modern portfolio theory is the most prevalent approach (Beketov et al., 2018). In this approach, an optimal portfolio is constructed out of an investable universe according to fixed rules based on limited personal data such as investment goals and the desired risk level. However, this does not rule out a possible use of AI in the 'back-end', for example to estimate expected returns, variances and correlations between assets or asset classes, in a similar way to methods that fund managers can use.

[20] Optimal allocations are usually very sensitive to personal preferences and characteristics such as risk aversion and investment horizon. These preferences are generally hard to elicit from retail investors via automated interfaces. Against this background, Bianchi and Briere (2021) argue that increased personalisation potentially introduces new parameter estimation errors, instead of reducing them.

[21] Cf. Article 22 of the Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 (General Data Protection Regulation).

[22] For academic interest in how AI can be used in robo-advisors, see, for example, Xue et al. (2018) and D'Hondt et al. (2020).

[23] Drawing from recent developments in the AI services sector, an example of a potentially transformative tool is ChatGPT, a chatbot launched by OpenAI in November 2022. The tool quickly garnered attention for its detailed and articulate answers across many domains of knowledge. Although the use of this or similar natural language generation tools by asset managers and other securities market participants appears to be still limited, advances in this technology may, in the future, change that picture. An uptake of these tools may come with increased reliance of the RegTech ecosystem on the models developed by few leading technology companies.

client's needs. In addition to the desired output, some firms also provide their clients with analysis or tools specifically aimed at interpreting it.

In fact, there is a broad consensus among firm representatives that providing 'explainable' tools – that is, tools that can be understood by their clients regardless of the complexity of the models employed – is critical to the success of their businesses. As some firm executives pointed out, a motivation for this is that clients are often wary of the role of AI in the asset management industry, which they tend to associate with excessive automation of the decision-making process, and are keener to accept its outcome when it is presented as providing 'recommendations' rather than 'decisions'. More generally, firm executives demonstrated awareness of the importance of enabling their clients to have oversight of and control over the models, data and processes employed.

On the one hand, these third-party providers serve a positive function, as they provide less sophisticated market participants with access to more efficient tools, which should ultimately improve market efficiency and generate economic surplus at a system level. On the other hand, it can be argued that outsourcing key functions of an entity's core business entails some risks, especially if these functions are delegated to potentially opaque systems run by a limited number of firms, thereby hindering clients' oversight of and control over the models, data and processes employed.[24] However, these risks are not inherently unique to the use of AI and can be mitigated through proper and efficient outsourcing processes.[25]

Explainability: finding the right balance

In the asset management industry, AI practitioners and observers often discuss the issue of the explainability of their algorithms.[26] To dispel lingering wariness among some clients and regulators regarding the adoption of innovative AI and ML tools, asset managers seek to dismiss concerns that AI may be applied as a 'black box' in the investment process.

Surveyed industry executives were unanimous in stating that AI is not tantamount to autonomous decision-making without human oversight. Instead, AI practitioners maintain that the best results are obtained when AI is combined with human judgment, and significant efforts seem to be directed towards developing solutions that provide insights into the process leading to the output of an AI algorithm along with the algorithm itself.

Nevertheless, some ML models that are potentially useful for identifying patterns from past data, such as neural networks, generate predictions and signals that are inherently difficult to explain and interpret. This lack of interpretability makes it difficult to understand whether the model is capturing meaningful patterns or noise, with potentially adverse implications for not only model performance but also risk assessment (Bartram et al., 2021).[27]

Recently, progress has been made in what is known as explainable artificial intelligence (XAI), which may prove useful in facilitating the use of ML by providing methods for interpreting opaque models.[28] Although they aim to measure the

[24] In this respect, IOSCO (2021) notes that the concentration of expertise in the field of AI and ML may create an outsourcing risk if the sector relies on a small number of firms within this space. It advocates requirements for firms to understand their reliance on and manage their relationship with third-party providers of AI and ML, including monitoring providers' performance and conducting oversight of their work. The study finds that firms in the asset management sector use external providers of AI and ML to varying extents: larger firms mostly indicated that they develop and implement AI and ML in-house or in partial collaboration with other firms, whereas smaller firms often tend to revert to solutions offered by external providers.

[25] Relying on third-party services and outsourcing is not a new phenomenon in the financial sector. It has been subject to EU regulatory requirements and supervision for a long time, including through effective governance and risk management requirements and outsourcing provisions. In recent years, the ESAs observed growing interactions between incumbent financial institutions, FinTechs and Big Techs, driven by efficiency, competitiveness, and innovation purposes. The ESAs identified increased risks to operational resilience particularly in cases where the management of outsourcing lacks robustness (see ESAs, 2022).

[26] For a detailed discussion of explainability, see Textbox 2 and Dupont et al. (2020).

[27] The current EU investment fund regime already contains transparency provisions that, in principle, prevent 'black boxes', making management responsible for overseeing the general investment policy, the specific investment strategies and funds' individual limits, as well as for monitoring risk management. Tomanek (2021) argues that, in order for management to perform the above tasks properly, they must be able to understand and question the decisions made. Consequently, some level of explainability of the AI systems used should be a condition for their application.

[28] See, for example, Linardatos et al. (2021) for a literature review.

dependency of the output from individual features, these solutions generally appear more limited than the statistical inference tools available for econometric models.[29] In robo-advisors and other use cases in close contact with consumers, the opacity of the systems that investors face may have a negative effect on their trust towards these systems.[30] Although AI-based systems may exacerbate this risk, the issue is arguably not specific to AI: it may also have its roots in the broader automation component and the absence of a human advisor.

TEXTBOX 2

Explainability of artificial intelligence

The explainability of AI, in its strictest sense, refers to a technical, objective understanding of an algorithm's behaviour, such as the possibility of determining the importance of various variables to the model's output. More broadly, explainability can relate to the notion of a given AI model being interpretable by and understandable to humans.

For instance, a linear regression model used for forecasting can be considered explainable, with the predicted output being a linear combination of the input variables according to weights determined via a specific estimation method, such as the least squares method.

Conversely, deep neural networks are typically regarded as scarcely explainable (or 'black boxes') because they are highly nested nonlinear models that transform data at each layer, producing a new representation as output through complex combinations of inputs.

However, the lack of a commonly shared, more precise definition leads to significant leeway as to what exactly explainability entails. For instance, one might consider a support vector machine (SVM) classifier, whose structure is 'known', to be interpretable and thus explainable. At the same time, if one is mostly concerned with determining the importance of the various variables in the model as opposed to the model's structure, one might consider an SVM to be hardly interpretable and explainable.

Hence, explainability must be put in context to define its actual purpose in finance applications. The 'explanation' of a specific result or of the algorithm's behaviour may prove necessary for end users (whether customers or internal users); in other cases, it will serve those tasked with the compliance or governance of the algorithm. To this end, Dupont et al. (2020) introduced four levels of explanation for AI in finance, suggesting that the appropriate level of explainability of an AI model should be determined based on the targeted audience and the associated business risk.

Trading

Various entities involved in the trading process make use of AI at different stages of the value chain. As shown schematically in Chart 3, the trade lifecycle can be broadly divided into three phases: pre-trade analysis, trade execution and post-trading.

The previous section of this article assessed how AI models can help asset managers and other investors analyse properties of financial assets to identify investment opportunities before a trade is executed. Other market participants, such as high-frequency traders, rely on algorithmic trading strategies that both take and execute investment decisions (investment decision algorithms).

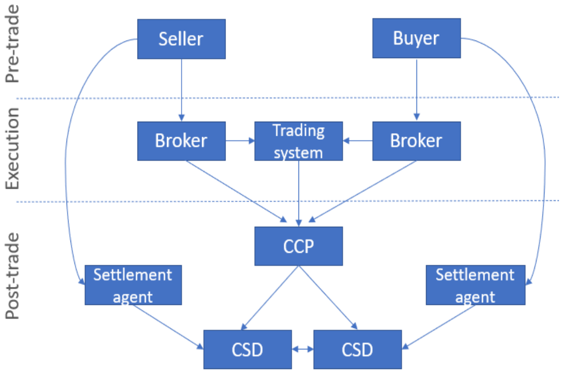
In other cases, especially when large orders are involved, AI can underlie specific trade execution algorithms that optimise the costs involved in the execution of a trade that has already been placed by minimising its market impact (i.e. the effect of a trade on market prices when it is executed). Finally, AI models can enable more efficient post-trade processing, for example by optimising the allocation of liquidity in the settlement cycle.

The following subsections explore use cases of AI respectively in pre-trade analysis and investment decision algorithms, in trade execution, and in post-trade processing.

[29] Using explainable algorithms may become a matter of practical importance if future regulations were to impose stricter requirements on, for instance, risk management and the prevention of possible systemic risks. Tomanek (2021) argues that, if UCITS and alternative investment funds were to underlie the same regulatory standards as investment firms subject to MiFID II, asset managers would be obliged to regularly check the proper functioning of their trading systems and trading algorithms, as well as review, assess and validate their algorithmic trading strategies on an annual basis. See also the discussion on algorithmic trading in the following section.

[30] Some studies show that interpretability influences users' perception of the accuracy of an AI system (see Nourani et al., 2019).

Chart 3
Trading process
The trade lifecycle comprises three main phases



Note: CCP, central clearing counterparty; CSD, central securities depository. The figure shows the main stages of the trading process. The actual stages and entities involved may vary depending on a number of factors, such as the firm and the asset class, and might entail a number of sub-phases or intermediate steps.
Source: ESMA

Pre-trade analysis and investment decision algorithms

Before a trade is executed, investors leverage AI models to analyse signals in asset prices and identify investment opportunities. This pre-trade analysis can either be subsequently evaluated by a human decision-maker (which is often the case in investment funds – see the section on asset management) or be part of algorithmic trading strategies devised to both take and execute investment decisions. These investment decision algorithms are typically used by high-frequency traders involved in market making and arbitrage, but also proprietary traders, quantitative hedge funds and other buy-side investors.

Overall, FMSB (2020) reports that most algorithmic trading that banks and large non-bank market makers conduct is still built around relatively transparent rules-based models. According to other recent accounts, many large proprietary trading firms have integrated ML models in their trading algorithms, albeit mostly in the form of supervised learning, with some experimentation ongoing around reinforcement learning (see Textbox 1). Where it is deployed, ML is primarily used to trade equities, futures and foreign exchange instruments, i.e. liquid instruments for which plentiful and timely data is available.

AI can support trading algorithms with the specific objective of reducing the market impact of trades: the use of AI for this purpose is discussed in detail in the following subsection on trade execution.[31] As regards the use of AI in securities pricing algorithms, examples include models to optimise hedging and quoting decisions. Some brokers rely on ML models fed with client-related past data (such as the historical 'hit ratio', which defines their relationship with the client) to automatise their response to clients' 'requests for quote', optimising their price and the probability of the client's acceptance.

Another promising area of application of AI concerns the pricing of securities lending transactions. Securities lenders must address thousands of inquiries daily regarding the available securities inventory for short selling. To compete, they have to rapidly respond to price inquiries despite high uncertainty regarding both the demand for and supply of the securities. Some lenders are increasingly using AI to solve two problems: setting optimal securities lending prices and predicting which securities will transform into 'hard-to-borrow' (HTB) securities.[32]

For the first purpose, some rely on models such as random forest (see Textbox 3) and polynomial regression, feeding them with a large number of variables reflecting, among other things, market capitalisation, utilisation, duration, and convexity.[33] To tackle the second problem, some lenders exploit supervised clustering algorithms such as the k-nearest neighbours (see Textbox 3) to predict the HTB status of a security, relying on the similarity of the features of the security

[31] ML methods can be used to estimate the market impact of a trade as part of both investment decision algorithms and execution algorithms from different perspectives: in investment decision algorithms, the market impact and other transaction costs are estimated alongside future price forecasts to predict whether a given trade is profitable; in execution algorithms, the market impact is estimated to minimise the transaction costs of an order that has already been placed (and possibly to respect a deadline by which it has to be filled).

[32] HTB securities are securities whose supply is limited for short selling. Naturally, they carry higher fees when borrowed for short selling.

[33] Utilisation is defined as loaned shares divided by available shares in the securities lending market, expressed as a percentage. The duration is quoted as the percentage change in price for a one percentage point change in interest rates. The duration of a bond is primarily affected by its coupon rate, yield, and remaining time to maturity. Convexity is a measure of the curvature in the relationship between bond prices and bond yields.

being analysed to those of securities whose HTB statuses are already known.[34] In addition, some lenders are exploring the possibility of using NLP techniques to process potential borrowers' enquiries, thus automating the initiation of the negotiation process.[35]

Trade execution

AI finds some of its most promising applications in the trade execution phase, as also reflected in the academic literature.[36] In filling an order, a broker attempts to minimise the costs stemming from its market impact, which is the most material transaction cost.[37] Accurately estimating market impact has become particularly important for investment banks and other brokers operating low-margin businesses.[38] Nevertheless, this quantity is notoriously hard to model, especially for less liquid securities, for which data on comparable past trades is scarce (see FSB, 2017). In addition, these market effects are nonlinear, meaning that they tend to be more than proportionally larger for 'metaorders' (i.e. large trading orders that are typically split into multiple 'child orders' and filled over several business days).[39] Some brokers and large buy-side investors such as pension and hedge funds have developed ML models to split and execute metaorders optimally across different trading venues and times, so to minimise their market impact and thus transaction costs. This optimisation task is well suited for reinforcement learning, which can be used to determine the optimal size and execution time of the various child orders of a metaorder.[40]

However, one main challenge these models face is the scarcity of specific data on metaorders, which only the entity filling the order possesses.[41] This has led brokers to develop models that are trained on a narrow information set and whose usability is thus very limited. Efforts are ongoing to pool data, although these initiatives are subject to data privacy concerns.

A solution contemplated by some asset managers is transforming the pooled data via techniques such as principal component analysis or the use of synthetic data. However, some of these techniques could potentially reduce the explainability of the models, limiting the ability to discern the effect of each variable on the outcome.

Lastly, market participants seem to increasingly rely on nonparametric models, which may better capture the nonlinear market effects of large trades. In this context, industry practitioners find that deep learning models such as neural networks or Bayesian neural networks outperform parametric models such as the I-Star model.[42]

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34 In this case, securities whose HTB status is unknown are the new observations, whereas the k-nearest neighbours' model is constructed on past securities whose HTB status is known.

35 See, for instance, Seagroatt (2017).

36 In this regard, see the work of Chan and Lakonishok (1995), Keim and Madhavan (1995), Farmer et al. (2013), Obizhaeva and Wang (2013), Said et al. (2018), Bucci et al. (2018), Lehalle and Neuman (2019), and Chen et al. (2022). For a formulation of the mathematical problem concerning the optimal execution strategy, see Alfonsi et al. (2010). For a concise explanation of the transaction costs stemming from market impact, see Briere et al. (2019).

37 Market impact has been estimated to make up around two-thirds of the trading costs (FSB, 2017). Some authors argue that estimating market impact costs is a significantly more daunting task than finding minimal profitable predictive signals (see, for instance, Kearns and Nevmyvaka, 2013), which demonstrates the potential gains available to market participants that can design superior models.

38 In this context, transaction costs are more likely to completely erase potential gains stemming from minimal price signals; see Haldane (2014). These considerations are reinforced by the requirement in MiFID II for investment firms to take all sufficient steps to obtain the best possible result for their clients when executing orders, taking into account the price, the costs, the speed, the likelihood of execution and settlement, the size, the nature and any other consideration relevant to the execution of the order (see Article 27 of the Directive 2014/65/EU of the European Parliament and of the Council of 15 May 2014 (MiFID II)).

39 See, for instance, Farmer et al. (2013).

40 For an academic study detailing a related model, see Chen et al. (2017).

41 This is information concerning the interplay between the actions the trader takes and the response of the security in terms of volume participation rate, price, minimum fill sizes, and residual average daily volumes (see Chidley, 2022).

42 For the notion of parametric versus nonparametric models, see Textbox 1. For an academic perspective on how parametric modelling can be exploited in the execution phase, see Park et al. (2016). I-Star is a parametric model that estimates the price impact in terms of known parameters such as price volatility (over a given period), participation rate, and average daily volume (see Kissel Research Group, n.d.).

Post-trade processing

Post-trade processing comprises the reporting, clearing and settlement of a transaction.[43] In this context, ML methods are used by some central securities depositories (CSDs) and brokers to predict the probability of a trade not being settled given the resources allocated to it, so as to optimally distribute said resources (namely liquidity).

The 'failed' or 'successful' label assigned to each past trade of a client provides an ideal supervised learning set-up. Models are thus calibrated on the past, labelled, client-specific data in a supervised learning fashion, whereas new clients, for whom past data is unavailable, can be assigned to clusters of existing clients through unsupervised learning techniques. Against the backdrop of cash penalties imposed on settlement fails envisaged under the CSDR,[44] research on ML models to improve post-trade processes is likely to bring substantial advantages to market participants and increase settlement efficiency.

Notwithstanding the nascent applications of ML in settlement activities, feedback received from central clearing counterparties (CCPs) and CSDs surveyed by ESMA suggests that, at least for the time being, most of these entities are not widely using AI. Indeed, investment in AI seems currently rather limited concerning CCPs, most of which argue that there is still limited additional value in the adoption of AI. Most representatives of CSDs pointed out that they are mainly still operating on legacy technology infrastructures that were developed over a lengthy period, yet are planning on expanding their use of AI in the near future.

Finally, some data reporting service providers (DRSPs) and trade repositories (TRs) have either deployed or started to develop AI solutions (based on ML models or NLP) for anomaly detection, data verification, data quality checks, and automated data extraction from unstructured documents. For these purposes, DRSPs and TRs tend to turn to cloud services offered by third-party providers. When asked about the main advantages of using AI, these entities stated that they expect improvements in terms of efficiency and accuracy, as well as facilitating decision-making.

TEXTBOX 3

Machine learning: some popular models

Random forests. Random forests are supervised learning algorithms that build multiple decision trees on randomly selected samples of the training data. They can be used for either classification or regression. Random forests tend to outperform a simple tree model as they compensate for its tendency to overfit.

XGBoost. XGBoost is a variation of the random forest model. It trains subsequent trees not on a subset of uniformly sampled training data, as in the classical random forest, but on subsets obtained by assigning more sampling weight to instances that are difficult to predict (i.e. instances that are not correctly classified by the ensemble of already trained trees). It tends to perform very well and is applied in many areas, including securities markets.

Neural networks. Neural networks are a type of ML that feature a series of node layers, including an input layer, one or more intermediate ('hidden') layers, and an output layer. Each node is connected with every other node from both the previous and the next layer, and has an associated weight and threshold. The output of a node is determined by the sum of all the inputs, weighted by the weights of the edges from the inputs to the node. If the weighted input is larger than the thresholds specific to the node, then the node is said to be 'activated' and will thus produce an output and pass it on to all nodes in the next layers. Conversely, if the weighted input is lower than the node's threshold, the node is not activated. Neural networks with more than one hidden layer are referred to as deep learning (see Textbox 1).

Clustering. Clustering entails grouping a set of observations that are homogeneous with respect to one or more given features. Clustering is usually part of exploratory data analysis. It can be either supervised or unsupervised. Supervised clustering leverages the existing classification of the observations belonging to the training set in order to classify new observations. A popular and intuitive supervised clustering algorithm is 'k-nearest neighbours', where the class of a new observation is determined by the already known classes of an arbitrary (yet usually small) number of its neighbours. In unsupervised clustering, on the other hand, the classes of observations belonging to the training set are not known, so clusters are determined based on other, known features. A popular unsupervised clustering algorithm is 'k-means clustering', where, in an iterative process, n observations are partitioned into k clusters, each observation being assigned to the cluster with the nearest mean.

[43] Clearing means the process of establishing positions, including the calculation of net obligations, and ensuring that financial instruments, cash, or both, are available to secure the exposures arising from those positions. Settlement refers to the completion of a transaction with the aim of discharging the obligations of the parties through the transfer of cash or securities.

[44] Regulation (EU) No 909/2014 of the European Parliament and of the Council of 23 July 2014 (Central Securities Depositories Regulation).

Other entities

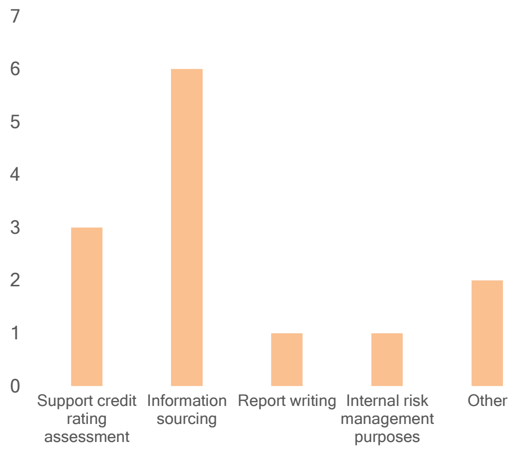
Credit rating agencies

Although some credit rating agencies (CRAs) stated that they do not use AI at all, most of the entities surveyed by ESMA are exploring AI applications. Yet, for the time being, this use appears to be mostly confined to the sourcing and processing of large quantities of data (see Chart 4). CRAs are using a variety of tools for these purposes, among which they mentioned NLP, clustering techniques, Bayesian statistics, natural language generation, deep learning, text extraction tools, and boosting algorithms (e.g. XGBoost).

For instance, some CRAs use NLP methods to process information scraped from the web and, in one case, support analysts in their drafting. CRAs seemed unanimously resolute in stating that, for the time being, they are not implementing AI to automate the credit rating assessment process. This is not surprising, given that credit ratings issued by CRAs are based on a combination of quantitative tools and expert judgment.

At the same time, some of them expressed interest in AI tools in the market and expect many actors in this space to increasingly look to digital solutions to support credit rating activities with reliable and timely data. In general, many CRAs predict the role of AI in the credit rating industry will grow in the next few years, fuelled by efficiency and precision gains. CRAs pointed out several challenges in rolling out AI extensively in the short term. These range from the regulatory uncertainty surrounding the implementation of AI to the large investments needed to acquire adequate expertise and technological infrastructure.

Chart 4
Activities performed with AI by CRAs
CRAs use AI mostly in support functions



Note: The chart is based on a survey sent to 24 CRAs based in the EU in April 2022. Eleven CRAs provided their responses to the question "Does your entity make use of AI to perform one or more of the following activities?".
Source: ESMA

Proxy advisory firms

Some proxy advisory firms use AI to gather, synthesise and process the information they use to provide institutional investors with research and data, as well as voting recommendations in shareholder meetings. In particular, the demand for ESG-related analysis from the industry and other stakeholders (see the section on asset management) seems to be driving the development of AI tools by these firms.

For instance, methods such as web-scraping publicly available documents and NLP can generate ESG assessments. By contrast, the surveyed proxy advisory firms stated that AI does not currently contribute directly or autonomously to the provision of voting recommendations to clients.

Some research has been observed around the development of NLP-based tools that could facilitate institutional investors' voting decisions, benefitting the process of shareholder activism by encouraging informed participation and dampening the drive towards robovoting (see Carpenter and Poon, 2018).[45]

[45] 'Robovoting' is a phenomenon whereby institutional investors rely on proxy advisors' recommendations without evaluating their merits or the analysis underpinning them when exercising their shareholders' voting rights.

Potential risks

An increasingly pervasive use of AI in the financial system is commonly associated with a number of potential concerns. Some of the main risks that AI entails in the context of securities markets are the following:

- explainability;
- concentration, interconnectedness and systemic risk;
- algorithmic bias;
- operational risk;
- data quality and model risk.

Most of these risks are not inherent to models or algorithms branded as AI. However, they can be amplified when using AI, as AI systems typically operate at greater scale, complexity, and automation than traditional statistical tools.

Explainability is arguably one of AI's most distinctive risk factors, in particular for some specific ML models (see the related discussion in the section on asset management and in Textbox 2). The lack of explainability of an AI model may potentially impair model performance and risk management.

At a systemic level, a growing uptake of AI in securities markets entails concentration risks. A number of observers consider it possible that – as making substantial advances in the development of AI systems is resource intensive – barriers to entry may arise and lead to outsourcing to the few large asset managers with the resources to invest in technology, data, infrastructure, and talent.[46]

At the same time, it should be noted that concentration and interconnectedness risks due to the dominance of certain providers apply to the broader digital financial services sector, as highlighted in the European Supervisory Authorities' Advice on Digital Finance (ESAs, 2022). Prenio and Yong (2021) warn that over-reliance on third-party service providers could also lead to commercial capture and dependency risk.

Some studies argue that the concentration of AI tools among a few systemically important providers may give rise to systemic risk, especially in the context of algorithmic trading, by inducing herding behaviour, convergence of investment strategies, and uncontrolled chain reactions that exacerbate volatility during shocks.[47] Relatedly, FSB (2017) notes that correlated risks from many financial market participants using similar ML models might endanger financial stability. This risk could become important with greater adoption of successful algorithmic trading strategies, although we lack concrete evidence to date that AI is precipitating this process.[48]

Although these risks have yet to materialise, it is interesting to note that the current European investment fund regime does not comprehensively address issues such as market concentration of the type described above, possible systemic risks arising from the use of AI in algorithmic trading, as well as algorithmic bias and overfitting (see Tomanek, 2021).[49]

46 A survey of finance professionals revealed that only large firms could afford to dedicate the resources necessary to implement fintech methodologies that have uncertain cost–benefit trade-offs at this stage of their development, such as those based on AI (see CFA Institute, 2020). This may also be true of entities involved in post-trade processes, namely CSDs and CCPs (see ESMA, 2021 and footnote 48).

47 MiFID II defines algorithmic trading as "trading in financial instruments where a computer algorithm automatically determines individual parameters of orders such as whether to initiate the order, the timing, price or quantity of the order or how to manage the order after its submission, with limited or no human intervention" (Article 4(1)(39)). WEF (2019) argues that off-the-shelf algorithms may converge towards a single view of the market, driving asset bubbles or magnifying market shocks. Tomanek (2021) argues that the UCITS Directive and the AIFMD – in contrast to the relevant provisions of MiFID II – do not mandate funds to adopt instruments such as automatic volatility interrupts or emergency interrupt schemes, which could effectively limit or prevent chain reactions. See Directive 2009/65/EC of the European Parliament and of the Council of 13 July 2009 (UCITS Directive) and Directive 2011/61/EU of the European Parliament and of the Council of 8 June 2011 (AIFMD). See also OECD (2021).

48 Although the possible adverse effects of algorithmic trading may be exacerbated by the use of complex, opaque, or fast-updating AI models, these risks do not necessarily originate from the use of AI. In this regard, MiFID II already contains provisions addressing the risks of algorithmic trading. ESMA has regularly monitored these risks and conducted exchanges with relevant stakeholders in the EU financial markets. As regards possible novel risks, ESMA's review report on algorithmic trading states that "most stakeholders could not identify risks and impacts on market structures other than those already mentioned in MiFID II that would deserve further regulatory attention". At the same time, the review also states: "A limited number of responses considered that only the largest market participants can keep up with the heavy investments required by the current technological 'arms race'. This not only reduces competition, but also leads to a concentration of risks in a small number of firms (including CCPs)" (see ESMA, 2021, paragraph 30).

49 Overfitting occurs when, due to an excessive number of input features or a lack of regularisation, a given model

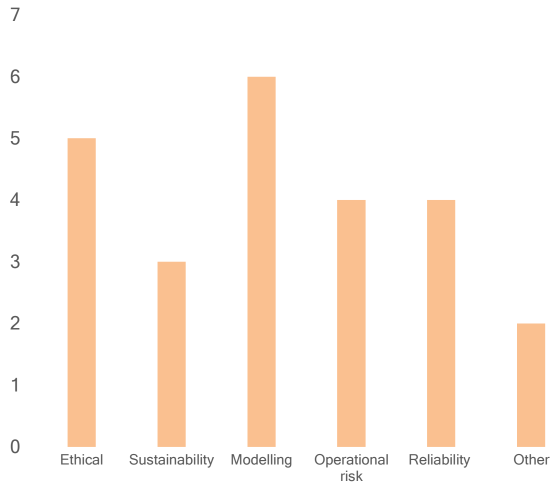
Algorithmic bias is, in fact, an often-mentioned concern when AI influences financial decision-making. The term refers to a systematic behaviour of an algorithm creating outcomes that can be considered unfair – for instance because they penalise certain individuals based on biological features – and that may be different from the algorithm's intended function.

Algorithmic bias can emerge from the design of the algorithm or from the way the data is collected and used. Compared with applications in banking and insurance, where the use of clients' personal data is inherent to activities such as lending, credit extension and consumer finance, there may be less risk of algorithmic bias in an AI model leading to discriminatory outcomes in asset management and securities markets. [50]

However, certain forms of bias can potentially distort the results of an asset allocation model, leading to suboptimal outcomes or posing a threat to the integrity of the market. For example, an AI algorithm may overweight stocks of firms with certain characteristics that happened to be correlated with outperformance in the past, but the use of which is discouraged in the present, such as the chief executive officer's ethnicity or gender.

When asked about the risks that they consider to be relevant when AI is used in the context of credit rating operations, several CRAs mentioned model risk, operational risk, ethical concerns and reliability issues (see Chart 5), with some entities adopting measures to actively pre-empt those risks, such as robust quality assurance. However, in line with the still limited role of AI in their current business model, CRAs stated that these risks had yet to materially affect their activity. In general, the systematic use of AI models in securities markets may exacerbate the operational risk resulting from inadequate internal control processes or from external events (e.g. cybersecurity risk).

Chart 5
CRAs' views on AI risks
Diverse risks considered, but yet to materialise



Note: The chart is based on a survey sent to 24 CRAs based in the EU in April 2022. Eleven CRAs provided their responses to the question "What do you consider the key risks of using AI in credit rating operations?". Sustainability concerns refers to the energy consumption linked to distributed ledger technology.
Source: ESMA

Finally, a widespread concern is that the quality of the datasets used in the learning phase can have a material impact on the outcomes and performance of AI and ML applications (see IOSCO, 2021). Industry experts often stress the crucial role of data as a necessary condition for taking advantage of AI. In short, AI depends on data as its 'fuel': the success of AI tools is highly dependent on data quality, and poor-quality, noisy data can easily result in unreliable models.

Although the use of AI is not yet pervasive in securities markets, the risks mentioned above warrant further monitoring in the light of the high levels of interest and attention that market participants generally devote to the topic. At the same time, appropriate governance and oversight of the processes in place are likely to prove effective in mitigating a substantial part of these risks.

cannot distinguish noise from a trend or pattern. Overfitting reduces the predictive ability of a model on unobserved data. The extreme flexibility of certain models, for instance deep neural networks, makes them prone to overfitting.

[50] For considerations regarding algorithmic bias in the insurance sector, see EIOPA (2021).

Conclusion

Promising AI use cases in securities markets are numerous, although the actual level of implementation varies both between sectors (depending on the business case for the use of innovative AI tools) and among entities in the same sector (depending on a number of factors, such as company resources and business models).

NLP is becoming widespread in all sectors where entities can gain an advantage from processing large amounts of text to identify specific unstructured information that may not otherwise be available, such as ESG policies, or conduct sentiment analysis. In asset management, an increasing number of market participants leverage AI in the investment process, for risk management and for compliance activities, either developing AI-based tools internally or sourcing them from external providers. Nevertheless, we find that investment funds that disclose and advertise the use of AI as part of their investment strategies remain few, suggesting a gradual uptake of the technology in the sector.

Although not yet pervasive in the trading life cycle, AI is also delivering concrete benefits there, from the execution of trading orders to post-trade processes. In execution, ML (especially reinforcement learning) allows brokers and large institutional investors to minimise the market impact of large orders by determining how to optimally split them between venues and periods. In post-trade processes, some CSDs are leveraging supervised learning to predict the probability of settlement failures and optimally allocate liquidity. However, surveys conducted by ESMA suggest that most CCPs and CSDs are not currently relying on AI models.

In other segments of the market, CRAs and proxy-advisory firms are exploring AI tools primarily for information sourcing, whereas experimentation with models that support key areas of their business appears to be still confined to a few entities.

Overall, although market participants increasingly use AI to support certain activities and optimise specific phases of their business, this does not seem to be leading to a fast and disruptive overhaul of business processes. This is due to a variety of factors, among which not only technological constraints, but also clients' preferences and regulatory uncertainty play a role.

Regarding the interplay between industry practices and the current regulatory framework, market participants surveyed by ESMA generally did not identify substantial barriers to the deployment of AI-based technology rooted in the current regulatory landscape. Nevertheless, they welcomed the prospect of a clear framework for the effective and trustworthy use of AI to help decrease the wariness that many market participants still have towards its adoption.

Against this background, risks related to the use of AI in securities markets are material but appear to be still limited. Nonetheless, AI has the potential to make critical business and decision-making processes significantly faster, more complex, and seemingly less transparent, all of which are central concerns of regulation and supervision. Appropriate governance frameworks ensuring the accountability and responsibility of both AI providers and end users are warranted in order to mitigate risks stemming from the complexity of some AI systems and the often massive volumes of data used.[51] Other risks may arise in the future if AI-based models become increasingly successful in investment and trading – for instance, from the concentration of AI systems in the hands of a few 'big players'.

Complexity and lack of transparency, although arguably not inherent features of AI, may, in fact, represent barriers to the uptake of innovative tools due to the need to maintain effective human oversight and upskill management. Some firms appear to be limiting or foregoing their use of AI and ML algorithms because of operational concerns such as the compatibility of AI and their legacy technology. Firms that do implement AI and ML tend to rely on existing governance and oversight arrangements and do not employ specific compliance personnel to challenge and oversee the development of ML algorithms (IOSCO, 2021).

In light of these circumstances, ESMA will continue monitoring AI developments and analysing related material risks to ensure these are well understood and taken into account.

[51] For detailed discussions of AI, data, and model governance, see Dupont et al. (2020) and the final report of the Artificial Intelligence Public-Private Forum (2022).

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Appendix: Analytical methods

ESMA's assessment of the use of AI in securities markets is based on information collected via several channels between April and November 2022. A number of interviews were conducted with market participants, including asset managers, institutional investors, brokers, financial service providers and proxy-advisory firms. Written questionnaires (with answers to be provided on a voluntary basis) were sent to entities directly supervised by ESMA (that is, CRAs, DRSPs and TRs) and to EU CCPs.[52] Two dedicated workshops were organised at which industry experts, academics, regulators, and members of international organisations discussed the use of AI in asset management and in the trade lifecycle respectively.[53] For the use of AI by investment funds, ESMA elaborated on data collected from market data providers. The information gathered via these channels was complemented by an extensive cross-sectoral review of existing market intelligence, research, policy analyses, and previous ESMA work on related topics, such as algorithmic trading and FinTech. All of these activities were useful to gain insight into some relevant use cases and trends. However, the content of this article does not necessarily represent an exhaustive assessment of all current and prospective applications of AI in securities markets.

[52] We received feedback from 11 CRAs, 4 CCPs and 2 DRSPs/TRs. In addition, a survey was conducted among 13 CSDs in March 2021.

[53] None of ESMA's interactions with market participants was part of a formal supervisory activity.