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AI-Powered Investment Decision Support Systems: Building Smart Data Products with Embedded Governance Controls

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Abstract

This paper explores some of the possible investment decision support systems powered by artificial intelligence, what components they include and how they operate. Progressing further, we analyze how different artificial intelligence and machine learning bases algorithm types, using different initial data and solving different tasks from simple classification of predefined assets to high-level algorithmic decision generation and implementing task can be combined together and layered to obtain a hierarchical multi-module architecture of the investment decision support system, which would maximize the advantages and minimize the disadvantages of utilizing artificial intelligence methods in the context of generating synthetic market predictions by the investment decision support system. Another critical aspect of investment decision support systems is the aggregation and optimization of the raw signals received from the prediction modules into trading signals, actionable within the high-frequency trading framework and deployable by algorithmic trading systems. We muse upon the possible trading signals aggregation function types and optimization traffic routing from the aggregated trading signals up to the algorithmic trading systems.
Within the next decade or so, investment decision support systems, generating synthetic market predictions and supporting traders dealing with tradeable assets, financial markets and instruments, will be heavily augmented and empowered with Artificial Intelligence and Machine Learning innovative algorithms and techniques, much the same way as classical industrial production architectures operated and supervised within the boundaries of the predetermined parameters are augmented and supported by Industrial AI and Machine Learning algorithms nowadays. Some of the main stages of decision making on the part of such systems follow the stages of cognitive vision and cognitive speech to some extent, observing the abstraction level ontology from raw primary inputs, such as images, sounds and other sensory data information for cognitive vision and cognitive speech systems to more complicated systems patterns formed on the system cognitive level.

Keywords: Artificial Intelligence, Investment Decisions, Decision Support Systems, Smart Data Products, Data Governance, Embedded Controls, Machine Learning, Predictive Analytics, Risk Management, Data Quality, Model Governance, Explainable AI, Data Lineage, Real-Time Insights, Portfolio Optimization, Compliance, Automation, Financial Analytics, Data Security, Regulatory Requirements, Intelligent Automation, Data Stewardship, AI Ethics, Scalable Architecture, Performance Monitoring

1. Introduction

This chapter presents a broad overview of the growing importance of Artificial Intelligence (AI) in the area of investment decision support systems, highlighting the very recent trend of AI to be embedded into wider decision-making systems and processes. This chapter is designed to give a 'bird's-eye' view of this new wave of research in the area of investment systems in order to provide an increasingly detailed exploratory landscape of the present situation. In particular, the chapter highlights important areas of active research and provides glimpses of very selective detailed studies in these areas. As such, the chapter serves both as an introduction to the various specific topics covered in more detail in other chapters.
Interest in AI to help improve decision-making has greatly increased of late - for several reasons. Information and communication technologies have matured to the point where knowledge can be easily captured, repositories thereon built, automated means put into place for inferring new knowledge and communicating it back to an increasingly wide audience for use. Different concerns within the area of investments decision systems increasingly need to be integrated. For example, risk assessment often done using expert systems needs to consider additional information widely circulated using multiagent systems. Decision makers in different organizations need to work together in a coordinated manner pooling their resources. Cybernetic principles and regulatory mechanisms help structure this activity. Ethical considerations weigh more heavily on decision makers as decision-making for investments affects increasingly wider swathes of the general populations. AI provides tools to assist in embedding these considerations in the investment process. Regulations encouraging more public involvement in decision-making are also being framed, ushering in a new eco-system. As a consequence of these and other similar regulations and motives, the areas covered in this book appear increasingly relevant today. These activities are carried out both at the national and supra-national level. Several branches of AI are important and are applied at different stages of the investment decision process.

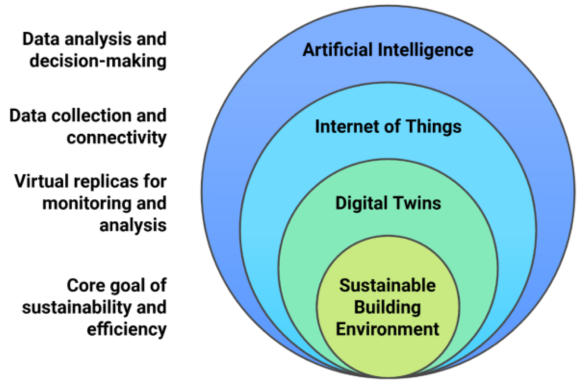

Fig 1 : Sustainable Building Environment

2. The Role of AI in Investment Decision Making

Artificial Intelligence (AI) has gradually infused our daily lives, shaping how we communicate, shop, travel, and invest. The impact of how AI affects investors' decisions is undeniable. There is more uncertainty in the world and investor's actions are no longer just a reflection of a rational person weighing up risks and potential returns. A deep understanding of how returns are generated is needed. It is important to note that humans can only get so far in predicting the future, because of these unknown unknowns. In order to overcome some of the limitations of traditional predictive models, we turn our attention towards AI. AI models, such as deep learning, can learn nonsensical representations that are optimal for prediction even when we cannot explain them. Furthermore, the models can be trained on enormous amounts of data and ignore all of the economic constraints that humans would usually put into their predictive models. In effect, this allows investors to put more trust that the model has learned the proper patterns in the data.

Investors are often inundated with overwhelming amounts of information, and their decisions are often clouded by personal biases. Machines with vast computational power, trained on information generally already available to the public, can quietly decide when to pull the trigger based on the ever-changing data stream, without the influence of emotion. Their investment decision processes can be encapsulated in algorithms, data-driven and optimally designed to make decisions in a similar way (and sometimes even better) than humans. In fact, algorithms are often recognized as the new Black Box, because they process information in a way that is no longer easily conceptualized by investors. Often, the decisions that algorithms make are also infeasible to test, due to the high dimensionality of the data as well.

3. Understanding Investment Decision Support Systems

Decision support systems have their genesis in operations research. The decision support systems for investments can be described as a hybrid of expert systems and knowledge-based systems supporting and complementing investment experts. They generally contain a knowledge base for capital market and individual investment products, a data base providing numerical values for investment portfolio evaluation updating, an inference engine enabling the decision support system to draw inferences pertaining to investment portfolios, and a graphical interface through which the user interacts with the decision support system. These characteristics indicate that investment decision support systems are a special class of knowledge-based systems whose functions are to support investment decision-making. Knowledge-based systems differ from traditional information systems primarily in their attempts to replicate human expertise. In contrast to classic information systems, knowledge-based systems use a knowledge base to manipulate data for the express purposes of providing advice or guidance on performance in areas so far thought far afield for computers to master.

Decision support systems have become a significant facilitation force in the data-heavy area of finance, and the new perspective of investment decision support systems helps better understand the facilitation that decision support systems provide in the investment decision domain. Unlike some of the earlier implementations of financial decision support systems, the new economic paradigm includes investment decision support systems covering a variety of investment vehicles such as equities listed on exchanges, corporate debt, government debt, derivative products such as options and futures, hybrid products, mutual funds, and portfolios of assets. We look at both stand-alone investment decision support systems and multi-purpose decision support systems that address a variety of investment and non-investment decision items.

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4. Data Products in Investment Management

Producing and converting information into actionable insights are at the core of investment management research and processes. Any technological solution applied to investment management has to deliver a tangible and measurable business value. As in other domains, such systems should deliver operational efficiency and allow intelligent management and facilitation of information flows. Research and investment management processes are cyclical in nature, centered on the recurring creation of financial products – investment recommendations, portfolios, and trading strategies.

Equation 1 : Investment Decision Function

$$D = f(X) = \sum_{i=1}^{n} w_i x_i + \epsilon$$

- D: Decision score or recommendation (e.g., Buy/Sell/Hold)
- x_i: Input features (e.g., market data, sentiment, financial ratios)
- w_i: Weight assigned to each feature
- ϵ: Model uncertainty or noise

There is a large variety of data products in investment management, generated through many diverse processes that operate at different frequencies. Report workflows generate periodic expert qualitative analyses and recommendations. Information-based investment recommendations, trade ideas, and allocation optimization workflows generate periodic qualitative market change recommendations and trading strategy ideas. Earnings forecast processes generate periodic consensus earnings estimates and analyses of forecast operations. News monitoring creates special event notification products. Earnings surprises monitor and report earnings distribution and surprise events. Recommended sell products signal potential position disposals. Corporate events and earnings releases provide periodic reports about scheduled events. Trading calendar products chronicle upcoming investment events. Statistical anomalies and price patterns workflows provide periodic technical trade ideas and strategies.

In practice, there are other domain-specific definitions of data products that capture full-spectrum qualitative and quantitative research effort outputs, spanning data, information, models, conclusions, recommendations, and other aspects prepared for eventual consumption by fund management. Nonetheless, the aforementioned list and descriptions encapsulate the most common data product types in the investment and research management domain. The generative processes vary by data product type, creating a taxonomy that considers information types, sender sources, and receiver users. For clarity, in Section 4.1, we reflect on data product taxonomies for supervised investment management practice.

4.1. Types of Data Products

The explosion of digital data and advances in data science allow for the construction of systematized Data Products that leverage information for generating economic value. Data Products that have been developed in the field of finance and investment management can be categorized into several types. The first type consists of raw data feeds, which process and distribute data that can be consumed by other systems or AI algorithms. Data feeds provide cheap access to information for a large number of users and may target different types of information, frequency, and latency. The majority of signal extraction problems in econometrics have been solved, and many Data Products are merely wrappers around existing data providers.

The second type is data aggregation and cleaning tools, which focus on applying filters to only provide "high-quality" data, for instance, removing outliers, correcting structural breaks, or interpolating missing values. By delimiting the type, frequency, or amount of noise in their data, aggregation tools can significantly lower the needed complexity for the final application, allowing the use of simpler algorithms and lower sample sizes, while at the same time increasing the chances of a successful final outcome. Finally, the third type consists of machine learning prediction systems that directly output a desired target using machine learning algorithms based on preprocessed data. Given the complexity of finance, Data Products that follow this route usually focus on very specific inputs, models, and outputs, such as equity price predictions in a given horizon, that rely on highly detailed relationships, and usually involve blending results from several machine-learning models.

4.2. Data Sources and Quality

The introduction of machine learning into investment decision support systems has fueled an explosion of new data products in the investment domain. There is a growing awareness that the performance of machine learning models is heavily dependent on the quality and heterogeneity of the data used to construct these models. Naturally, the design of these data pipelines plays an important role. In this section, we provide a survey of common data sources and data processing methodologies in the investment domain. The goal of this section is to provide a comprehensive summary of what are the source data products used to generate the training data and validation data, and how managers can leverage these data sources for their own in-house data pipelines. Investment management deals with a multitude of activities ranging from trade execution to portfolio optimization. Therefore, there is no single source of data in the investment domain. The information about portfolio performance and risk modeling is typically drawn from the respective fund managers, along with some additional verifiable statistical information from custodians. Price data is readily available from legacy data feed subscribers, and several other subscription services. In recent years, there has been a proliferation in price and liability-sensitive derivative data from providers using directly accessible files and solutions. Fee structure data for private equity funds is available, while hedge fund fees are difficult to source due to high variability and availability through hedge fund managers. In the last twenty years, Alternative Investment Market activity data has become increasingly available through the website.

5. Embedded Governance Controls

IR in its most sophisticated forms is possibly an adaptable, instrumentable, extensible, controllable, self-steering, operative, viable, ideational, multiagent, and multi-modularist set of "sub-governing controllers". It applies internal created incentive and motivation structures to the participants, capital resource owners and other users of this ecosystem to make the participants make IR their own, and thus act in the common best interest. It creates and promotes a self-governing, self-establishing institutional environment in which IR operates, thus optimizing transaction as well as governance and capital costs. IR aligns monetary, fiscal, security, pension, regulatory, trade, education, labor, and other incentives to bring about an information-dependent internal coupled equilibrium.
Embedded governance functionality within ES and AI is policy development and governance functionality possibilities and capacities to operationalize and enforce, monitor, and report on process and content governance embeddedness. Embedded, governed autonomic resource-affecting decision policy and standard setting, executing with pre- and post-decision audit monitoring and reporting are decidedly positive and necessary features of all IRs. These include the autonomic capability to exercise discretion, to deal and trade, to assimilate and accumulate capital resources in their various forms, and to assess and balance risks within prescribed limits and en masse as well as ex-ante and ex-post on a case-by-case basis.
Piloting the many ambient "turnkey" self-governing modules that come into play means that IR at its various levels and fields of specialization should have a "sub-governing controller" feature that implements policies in each case amid a highly flexible, adaptable module setting with monitoring and reporting. Embedded policy capabilities scope should encompass economic development, sustainability, stability, and business cycle needs in both their local as well as their global contextualized specifications that econometrically estimate the need, periodicity, and cyclicality features, as well as the temporal and possible inter-temporal stacked length over which autonomic decision taking requires steering and thus monitoring to take recommendations fulfillment with possible sanctions on IR decision support modules at all levels and in all settings.
This policy module is tasked with stimulating, sustaining, and steering the economy and/or holding it in recommended temporal, spatial, or inter-temporal balances on the defined targets of price-level manageability, monetary as well as fiscal prudence and sustainability, balance sheet management of the public authorities and its various sectors, both at home and with the international community, across a defined trade and balance of payments paradigm. Sustainability means not allowing an economy to deviate semester by semester for cyclical reasons.

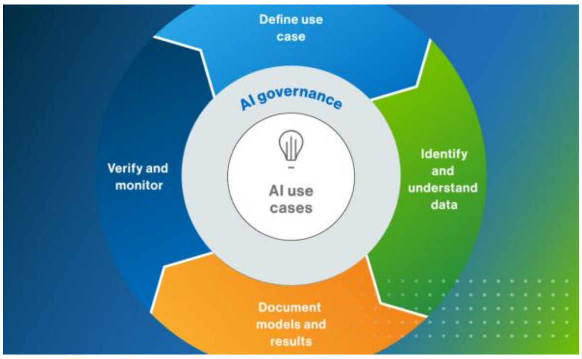

Fig 2 : AI Governance Framework

5.1. Definition and Importance

Investment decision support systems, particularly in AI, can contribute to better investment decisions, on average. By following the investment decisional model generated by an AI-PIDSS, one can achieve a better portfolio construction than by performing such a task without any support. Such a supplementary investment decision facilitation is possible based on general information and transfer functions predicted by AI-PIDSS.

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Even if the average result of using AI-PIDSS is a better decision than without its use, not all the decisions generated or supported by AI-PIDSS will be "good" in the sense of being better than the investor's level of tolerance of risk. This means that a number of poor decision outputs of the PIDSS are reasonable and acceptable, especially in times of extreme market events when the forecast errors created are likely to be the largest. The occurrence of a few wrong decisions, especially repeated ones, may lead to detrimental effects on the financial performance of the investors performing the decisions in question. As such, an AI-PIDSS should incorporate elements of governance mechanisms, which will be used to create a framework for the embedding of the investment decision support systems, namely the AI-PIDSS constraints or rules that have to be followed and included in its decisional process and output(s).

5.2. Framework for Governance

To understand embedded governance controls in decision-systems, consider five steps. First, AI researchers must show that AI is actually general or special enough to do useful things better than a human. Then, firm management has to decide whether to trust an AI or leave those decisions to a human. Decision-makers must then specify what goals and constraints are relevant in each situation, a process known as prompting. Thereafter, given the prompt, the AI needs to correctly weigh the situation variables in the prompt. Finally, humans must decide whether to follow the AI's advice for the decision to be embedded.

There are some potential pitfalls in this framework. A broader spectrum of tasks are outsourced to an AI whose generality has exceeded that of the human or a narrow range of tasks can be outsourced to the AI specializing on its own training sample but the management go-getter will generalize. The decision-maker might choose a prompt that is biased in terms of the relevant situation variables. The AI might not specify the correct weights for that prompt. Finally, the advisor decision usually needs to pass through an emotional filter before it is endorsed. The text offers two functions of governance roles. First, it sets the rules, goals, incentives, and risks to ensure that human and AI decisions produce an optimal joint action. Second, it executes the advisors' recommendations within the limits of the advice, or filters the advice for implementation through a human emotional lens on risk attitudes.

6. AI Techniques in Investment Systems

Artificial intelligence (AI) encompasses a diverse range of computational methods employed in investment systems. AI techniques in investment support systems could be grouped into machine learning techniques, natural language processing, and predictive analytics. Machine learning has gained wide acceptance in financial investment and prediction, with uses for portfolio optimization, security analysis, capital allocation, capital acquisition, and systematic trading.

Machine learning algorithms discover hidden patterns or structures from input data without using these patterns hidden in the data. Supervised learning or classification techniques are generally used when past data with known labels is available, applying learning techniques to build models that classify future inputs into specified labels; for example, buy, hold, sell labels for stock trades intended to maximize profits. Supervised learning is used for stock price prediction and prediction of macroeconomic variables, but requires the labor-intensive task of labeling data. Unsupervised learning methods, such as clustering techniques, do not require labeled data, but instead seek patterns within the data itself with no prior labels; these techniques can be used to group stocks with similar returns, for example.

Numerous machine learning techniques have been applied to various aspects of financial investment. Core techniques include parsimony methods, such as linear regression, regularization, and factor-based models; machine learning-specific techniques, such as boosting, deep learning, Gaussian processes, generalized additive models, knn, random forests, and support vector machines; and unsupervised techniques, such as clustering or other factor modeling techniques. Comparisons show that parsimony with a few factors tends to outpredict machine learning methods out of sample, even after hyperparameter tuning. However, machine learning methods apply best when training on recent data, with hyperparameter tuning. Thus, machine learning methods are better suited for backtesting or short-term improvements to core models. Financial natural language processing analyzes unstructured text data contained in business news articles, newspaper reports, social media, earnings conference calls, and capital investment reports, taking into account aspects such as sentiment, ratings, and entity recognition.

6.1. Machine Learning Algorithms

In the past years there has been a rapid increase of available transaction data in the Financial sector. High Frequency Trading platforms generate a huge volume of data and are able to reach a fast response by executing several buy/sell orders over an extremely short period of time. Other descriptive terms used to define such type of data are structured data, transactional data, longitudinal data or time series data, by stressing the presence of observation records at different time instances. Data from HFT platforms represent a significant fraction of trading in equity markets. In addition, other sources of non-structured data are available, such as corporate earning reports or news about unexpected national events that may influence the stock market. From a general perspective, the volume and variety of information about financial time series

oblige traders and investors to switch from the standard decision-making process to an AI-Powered decision-making process capable to extract the main correlations sophisticated machine learning algorithms.
From a general perspective, the task of retrieving useful and practical knowledge from data can be accomplished using Descriptive Modeling or Predictive Modeling or even both. From the analysis of previous literature develop in the field of AI support for the Investment Decision Support System, for both Descriptive and Predictive process a plethora of machine learning techniques has been applied or suggested in order to support the IDSS task in terms of using distinct algorithms for different user-defined stages. Without being exhaustive, the most utilized techniques for Predictive Modeling are as follows: Genetic Algorithms, Logistic Regression, Artificial Neural Networks, Random Forests, Support Vector Machines, and Time Series Models.

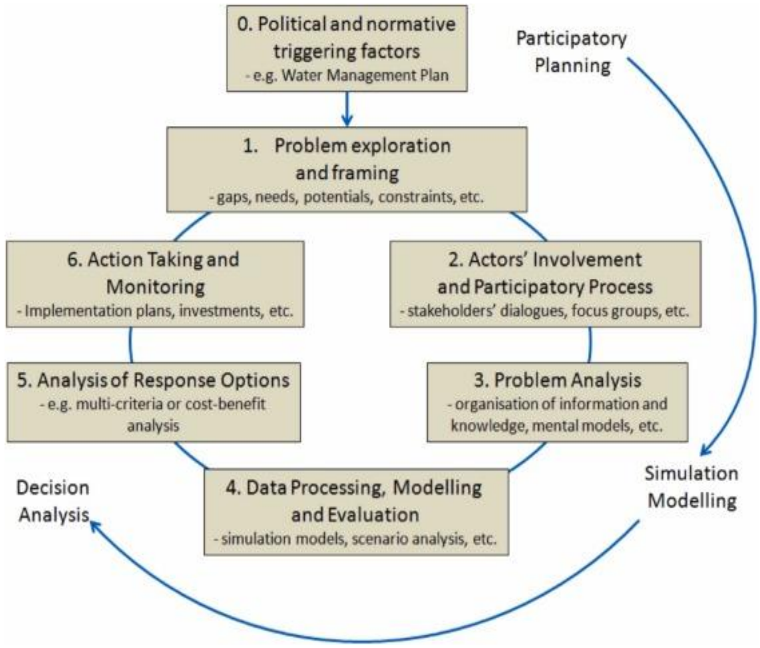

Fig 3 : AI-Based Decision Support Systems

6.2. Natural Language Processing

Natural Language Processing (NLP) refers to the branch of AI that is focused on the interactions between computers and human (natural) languages. More particularly, NLP is concerned with algorithms to process and analyze large amounts of natural language data, with the ultimate goal of enabling computers to understand and generate natural human language. As investment decisions are supported by large volumes of qualitatively valuable information, the successful application of NLP in financial markets opens the field for early improvements of decision making. NLP approaches are predicted to be used for a wider set of processes like corporate lifecycle process prediction, firm strategy prediction and identification, cash flow prediction, evaluation of cell towers business, early prediction of business decline and defaults from social media, prediction of the Mutual Fund routes and the HERFINDAHL index of the mutual fund industry, economic modeling with publicly available news releases, improved predictive modeling from news sentiment using sentiment databases, hedge fund positioning prediction using public press statements, increase in sentiment momentum prediction, price projection of the digital cryptocurrency using a Deep-Learning approach, prediction of Bitcoin price using Deep Learning approaches, sentiment analysis of financial news headlines. Consequently, one can talk about the fast and steadily rise of Data Science in Finance.
NLP attracting the interest of researchers and investors alike can also be seen in the increasing number of research papers and the commercial products available. While NLP and machine learning more generally have plenty of advantages, investment decision support systems have to offer more than only the possibility of a slightly improved prediction accuracy.

6.3. Predictive Analytics

Although typically used in relation to risk management systems, Predictive Analytics can also contribute directly to investment decision making. In this work we present an innovative Predictive Analytics solution, Smart Indices, which contributes to the creation of traditional passive indices in a more effective way, while enabling the design of novel types of factor indices and macroeconomic indices. Smart Indices were created to address the facts that traditional passive indices are suboptimal since they weight universe constituents equally or according to simple value metrics, and that many macroeconomic time series are commonly modeled through naive linear differencing approaches, with no seasonal adjustments or change point determination. More specifically, we propose our insample and out-of-sample macroeconomic time series predictions as factor that can be added to traditional return-based and macroeconomic factor portfolios already present in the literature.

The return-based predictive model uses the historical returns of assets in a given universe to find the best forecasting model within a pool of competing forecasting models, while the macroeconomic factor predictive model uses a weighted combination of the five best macroeconomic variables selected properly. The weights, or the coefficients of the forecasting models, are trained with the Adaptive Lasso method. There exists an innovative Dimensionality Reduction procedure that is used to deal with both overfitting and heavy frequency mismatch. Smart Indices can deal with multiple asset types and contribute decisively to asset allocation and selection, as well as for risk management and retirement investment planning. They provide signals based on time series econometric modeling and machine learning tools to decide on the tactical ways and the strategic ways of investing, while respecting investment policies during asset allocation periods. They are able to adopt a market timing approach in a few periods, and can be used in both single country and cross-country applications.

7. Building Smart Data Products

For a long time, research in finance has been mostly an academic affair. Financial decisions have generally been made based on novelty, constant re-optimization, sell and return predictions, for example, 'sell or buy' decision as an all-in action rather than as a gamble combination of risks and opportunities. Today there is a widening divergence between academic finance research on the one hand, and the deep learning and AI developments in other fields on the other. The financial toolbox is increasingly fragmenting into many specialized tools, whereas the underlying finance really needs to be seen as a continuum along the intrinsic bias-volatility axis of the different decision risk tools, which are generally operating at different decision period horizons. Moreover, building any product, such as in our case 'AI for Financial Products' for a client or a group of clients, needs particular caring. You need to care for the decision architecture, design, integration, and collection of tools, both at the macro and micro level. AI and deep learning products in finance need to be client and user-worthy.

Specialization and big data tools are in that domain probably both the most useful and the most dangerous. Very few things are as costly in a financial market as developing or offering a futile or a damaging product, such as prediction-based bonds prone to downgrades and ratings risk. Product development is in that space both client-sequence question and answer, and decision process innovation dependent. We make a clear distinction here between 'problems' from the client point of view and 'questions', which are specifically related to the set of decision period and decision time.

7.1. Design and Architecture

Based on our overall vision outlined in this book, our design proposal for Smart Data Products organizes the entire system into multiple modules (sub-products), each responsible for a specific task. The reusable modules can be incorporated into other investment decision-making systems as needed. Our choice of deploying a modular architecture is motivated based on three main factors: first, investment activities involve many diverse tasks and investment decision-making can be aided through closed-enough iterations among many of those tasks; second, it is easy to task partition and allow efficient load balancing since each task step can take different amount of time to finish even for similar training sizes of the input feature space; third, the components can encapsulate investor's proprietary knowledge, rule- and/or pattern-based objectives so that they can be devoted to classify or learn patterns through supervised or reinforcement learning.

It will be up to the user to choose the modules they want based on the design goals, to federate the data among those modules, and to create, if applicable, a group of design pipelines based on their investment-themed tasks. Each of those data modules extracts certain features from either raw or curated data as a building block for a Smart Data Product and chains those modules together to offer a unique investment solution. The modules can be categorized into several major pipeline groups. The data group is to provide the different kinds of clean data which serves as the input for other module groups or building blocks for building various niche investment Smart Data Products. The cleaning module focuses on removing the noisy parts of the data, while the enrichment modules are interested in impute missing values or interpolate over a period of time. The curation module is to offer curated data into the product. The market sentiment modules are creative rooms for developing Smarter Sentiment Products. The additional customized module can be tailored to directly address the user's need for data other than market and sentiment data.

7.2. Integration with Existing Systems

The multitude of data processing and investment support technologies developed and implemented in business operations entails the need to align new smart data product development efforts with existing solutions. To solve this problem, teams working on smart data products should collaborate closely with other teams responsible for the development and maintenance of existing business systems. If data product teams follow the outlined smart data product development roadmap, more often than not, they will achieve the result of how to add value to the existing system with little additional effort. However, the evolved capabilities, potential applications, and user benefits of the new technology of AI, how it empowers and augments data products that do things only grownups used to do, require business organizations to rethink their processes. In particular, the amount of human intervention, the various tasks different employees do at different stages of the investment cycle, and the business systems that hold relevant data, need to be redesigned. This often entails loss of expertise in some operations and addition of AI-powered data products in others. Getting the timing right for the organizational change to add new AI employees and reduce the value-added effort burden of their human predecessors requires close integration between the developers of smart tools and the participants in investment decision-making workflows.

The aim should be to achieve a continuous learning and improvement process, updating an organization's culture and organizational structure to fit the implementation phase of the new AI tool. Fortunately, the new technology of AI-Powered tools typically dictates an approach that allocates effort to people only at critical points, while the routine workflow for vast amounts of companies go through AI decision support tools, simply depending on crystal clear directives from decision-makers in charge of the critical decisions supported. The lack of disturbance in the typical workday reduces the threat of new AI-powered decision support tech. That frees both employees and management to address the change process.

8. Case Studies of AI in Investment Decisions

As we described in our discussion of AI-Powered IDSSs, these blended decision support systems combine their predictive power with prescriptive tools for selecting the best-performing stocks and mutual funds from among many potential assets. Candidate selection is initial, neither as granular nor as dynamic over time as later rebalancing decisions, but is enabled by the predictive tools. Candidate rankings for subsequent phases of heuristic decision-making, whether automated, human assisted, or human driven, can therefore involve hundreds, even thousands of candidate assets; ongoing prediction is therefore critically important to the overall success of using AI in any component of investment decision support. Such blended systems excel at facilitating portfolio holdings decisions over time, but success is only possible with a very high level of predictive performance. That performance is not only essential to avoid significant capital asset losses, which haunt both investors and investment companies, but to enable out-performance financial returns that are the lifeblood for sustaining many investment management companies operating today.

We also mention time-horizon differences because studies have shown that decision phases at various time horizons respond differently to predictive models and tools. Relative investability has been demonstrated to follow particular patterns over various time horizons, percentage investable at horizons shorter than one day to three months are relatively low and inversely related to time horizon, with spikes at one-year horizons as institutions unwind their portfolios for end-of-year accounting. Consequence unpredictability is especially important for higher frequency decision support; many hedge funds follow opportunistic strategies trading individual stocks in less than thirty days or even intraday; the algorithmic, AI-intensive trading that is the bulk of equity trading today is just such shorter time-horizon decisions.

Equation 2 : Smart Data Quality Score (DQ)

$$DQ = \alpha C + \beta A + \gamma T + \delta R$$

- C: Completeness
- A: Accuracy
- T: Timeliness
- R: Relevance
- $\alpha, \beta, \gamma, \delta$: Governance-assigned weights

8.1. Successful Implementations

A few successful implementations of AI-Powered Investment Decision Support Systems exist, spanning various aspects of the investment decision-space. For example, a proprietary AI-Powered Investment Decision Support System has been developed to help assess the risk of fixed-income investments, with capabilities that have since expanded rapidly to incorporate multi-asset classes. The system's capabilities focus primarily on portfolio construction, back-testing, optimization, execution, and risk management. The rationale for utilizing AI to enhance standard quantitative algorithms is that, despite the sophistication and extensive utilization of quantitative portfolio construction optimization algorithms, their effectiveness has diminished as capital markets have matured. AI algorithms are thought to find latent structure and lead to the identification of dynamically exploitable anomalies - anomalies that are undetectable using traditional econometric methods - and yield nearly instantaneous reactions to the cognitive errors of the greatest number of investors; namely, buy-and-hold investors influenced by emotional and behavioral biases.

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Furthermore, a chatbot has been deployed to assist investment banking and sales and trading personnel. This AI-Powered Investment Decision Support System is designed to access internal databases instantaneously, thereby outperforming human assistants while also providing a more intuitive user interface. The system can answer multiple questions posed in natural language, quickly providing answers to inquiries that previously required the assistance of a secretary. These inquiries might include: What IPOs are currently in the pipeline? Which were the last IPOs led by the bank? What were their performances during the first year after the IPO? What is the corporate family tree of a specific corporation, and what are the existing banks on the equity and/or debt transactions? Beyond enhancing proprietary efficiency, the system is also expected to improve advisory capabilities and ensure privacy, as clients can issue verbal or typed inquiries directly into their phone and receive the answers in the same manner.

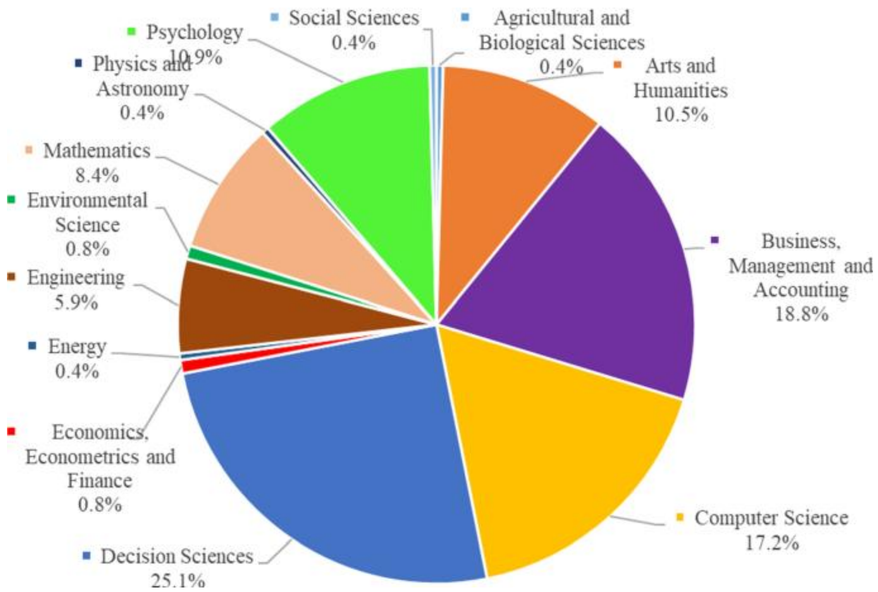


Fig : Artificial intelligence for decision support systems

8.2. Lessons Learned

In total, the 15 case studies confirm the increasingly expanding embrace of AI of various flavors in solving multiple facets of the overall investment decision support problem space. The nice thing about the case studies is that almost all of them reveal a nugget of "lessons learned" wisdom which could be helpful to other institutes and organizations in guiding their journey. Two lessons stand out. One, recognized by multiple case studies, is that AI has to co-exist with the often listed synthesized elements of domain expertise and human oversight and intervention. AI is still evolving in confidence and capability; it's not yet the holy grail of agency that totally replaces human engineers and managers. However, in the meantime, we are getting close as many of the solutions successfully leverage the reinforcement learning and AI-assisted decision automation approaches to do much of the heavy lifting often relegated to a human talent pool. Forward looking investment tech support organizations should take a holistic view on their structure and processes to invest in human capital and AI tools in concert. The second, oft repeated, lesson that echoes is that there is no one-size-fits-all solution to monetizing AI for investment tech. Partially, this is due to the still vast petri dish of approaches based on the available flavor of AI but also the different priorities of the volunteers and their personal chemistry. Moreover, AI isn't free and organizations often are surprised by the infrastructure costs so success often follows investment in eating the AI elephant a bite at a time to spread the risk and allow stakeholders to see the benefits while learning what works best in aspirational portfolio decisions to maximize their returns.\

9. Challenges in Implementing AI Systems

Artificial intelligence (AI) systems are a new, hot area of research and development. Widespread hype from both corporate leaders and government officials fuels interest. There are many questions about whether these technologies eventually will go on to break human level general intelligence, in the manner suggested by the more futurist fascination with AI. However, before we cross any such bridge, we must consider the pressing practical questions just downstream. There are important, and pressing decisions that need to be made about how to implement current AI technologies, the so-called narrow AIs. The perceived benefits and apparent excitement in implementing AIs cannot be taken at face value. A backlash against the implementation of AI systems is already developing. Some corporations are stockpiling multiple copies of each system on the market. AI systems are also managing high-finance sector operational workflows that control the flow of billions of dollars through international markets. The implementation of AIs to control these processes is viewed as an automated form of trickle-down economics. CEO's enjoy record-breaking stock dividends while their companies are not spending on anything else.

While there are many real, and serious, advantages claimed for AI implementation, there are numerous ethical challenges that need to be resolved in those areas where implementation is thought to yield real benefits. For example, in the cases of autonomous vehicles or personal home assistants. In addition to these more ethically grounded concerns, there are a range of technical challenges to the successful implementation of AI systems that span the entire design, development, and life cycle. A review reveals a range of technical challenges related to the design and implementation of AIs that influence the ethical challenges resulting from the deployment of AI systems.\

9.1. Technical Challenges

A number of technical challenges are associated with the actual engineering and deployment of AI decision systems in practice. It is crucial to note that AI systems are not magic black boxes able to solve any problem nor are they universally better at any task than traditional methods. AI systems introduce new external dependencies into the decision support systems they augment and repair, complete, or else are augmenting components of a larger hierarchical system. Transitioning to AI techniques will often require a period of evaluation and tuning of novel automated solutions to match expected accuracy and reliability levels before deploying these agents in the field. Because of this, there exist many interaction surfaces between the AI component and the overall investment decision process.

Performance concerns can arise in the course of experimenting and managing AI systems in practice. Risks typically associated with algorithmic execution in the field involve instabilities in predicted outputs, when operating outside the training regime with respect to timescale, funding universe, model, specification, or data quality. Operations in this hazard realm can lead to risks measured as high capital misallocation error due to incorrect predictive classification and clustering performance. An additional risk stems from over-specified, mis-specified, or poorly tuned models returning outputs that are persistently off target on the timescale of application (leading to punishing excess returns over an investment horizon). Other operational hazards stem from reduced representation in phase spaces causing loss of credibility by missing specific investment environments or asset classes resulting in output inversion. Finally, communication mismatches between AI capabilities and investment domain communication presuppositions may lead to suboptimal decision outcomes.

9.2. Ethical Considerations

Investment decisions are often framed in a rational and quantifiable manner. We carefully evaluate prospective time series patterns and develop appropriate investment strategies. After that, we simply implement and execute the strategies for making investment decisions. However, when we come to think about experiencing these investment decisions and the ultimate consequences, we realize that these decisions do not always match quantitative rationality, but are often related to psychological factors. Considerable existing literature has shown that the market may deviate from the efficient market hypothesis. Instead, perceived and imagined standard conditions, such as "fear of losing" and "fear of missing out", rather than the real market conditions, have caused price fluctuations different from predictable patterns. External socio-political events, such as wars, elections, and epidemics, can also create sentiments that significantly influence price changes. At such times, investment decisions lose their rational aspect and involve ethical considerations. For majority of investors, the purpose of engaging in capital market activities is for profit maximization. However, in making those decisions, constraints of morality and conscience come into play. In addition to financial success, investors are also concerned with the socio-political or environmental impacts, such as the welfare of vulnerable individuals or groups, the sustainable use of resources for future generations, and the sustainable management of the ecosystem to prevent its extinction. To some investors, it may matter whether causes, such as organizations for the promotion of democracy, are financially supported or whether there is any financial damage to the groups responsible for the refugee crisis. These worries may ultimately lead a subset of investors to consider whether the investment causing serious grievances, including modern slavery, are indeed producing any income for themselves.

10. Future Trends in AI-Powered Investment Systems

AI-powered investment decision support systems have been evolving and increasingly imposed their presence in the modern global digital ecosystems. What will be the next phase in these trends? In accordance with global tendencies of the current technological progression, the future success of these platforms can be determined by quantitative and qualitative performance of their application within requirements of digital economy. How well would they satisfy investor's demand for transparency, quality, and speed of investment decisions? How much would they increase profit while diminishing risk exposure? What technological and marketplace configuration would drive their functionality evolution? In this section, we will derive benchmarks for the future development by analyses of two aspects inherent in any universal system's evolution.

Emerging Technologies. Recently, a plethora of emerging technologies came to the stage of utilizing AI-powered investment decision support systems as their exclusive practical application or, at least, their primary market. The financialization of the digital economy has been pushing on ubiquitous demand for financial services from increasingly diversified and deconcentrated corporate clients. Moreover, in addition to satisfying their own requirements, they express readiness to give their data to the providers of the cloud-based AI-powered investment decision support systems to obtain specific data-driven investment decisions for a fee. Investment companies, banks, and managers have been aggressively shifting their investment processes to the algorithms, driven by the availability of massive public data, analytical market, and rewarding high performance capabilities of the Neural Networks Circus. The decentralization of finance would not eliminate the algorithms from the core investment process; at least not the companies with an extensive technological background that can leverage public blockchain and DeFi's protocols. It has been facilitating trustless investing by validating the investment transactions on the network, often based on the simple Smart Contract Law without complicating components packaged in complex algorithms.

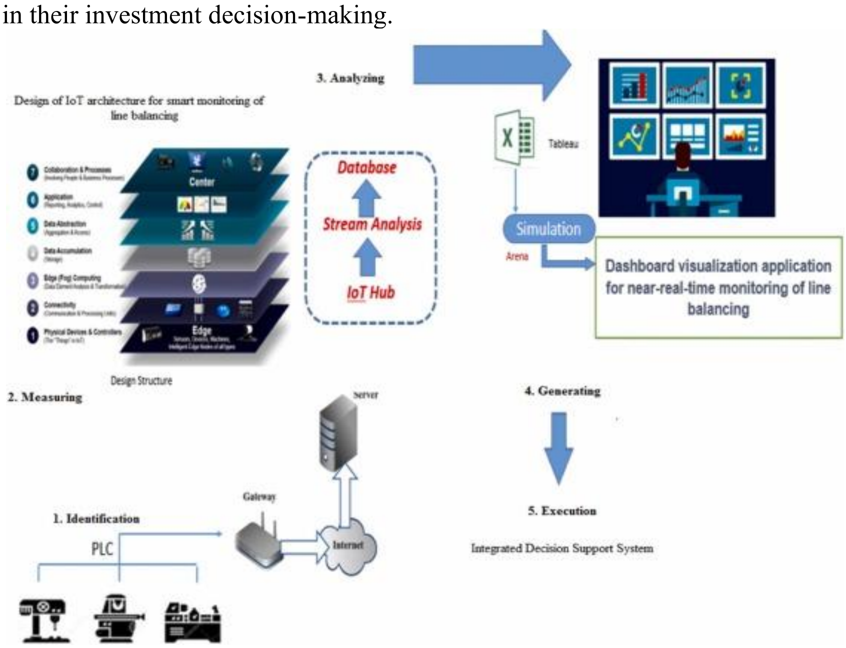
Equation 3 : Risk-Adjusted Return Prediction (Sharpe-like metric)

$$R_{\text{adj}} = \frac{\mathbb{E}[R] - R_f}{\sigma_R}$$

- $\mathbb{E}[R]$: Expected return from the AI model
- R_f: Risk-free rate
- σ_R: Standard deviation of returns (volatility)

10.1. Emerging Technologies

New technological solutions and hardware can dramatically alter the efficiency of investment processes. In the future, we will observe wider application of new hardware, like quantum computing and neuromorphic chips, making substantial improvements in many AI tasks feasible: from analysis of very large data sets and generation of risky scenarios to the training of deep neural nets with complex topologies and the real-time execution of very large reinforcement learning models. The speed of digital transformation in the financial markets will also speed-up the advent of novel solutions. We can expect a more rapid process of invention/deployment of AI solutions like the one currently observed with the use of actual Neural Networks and Reinforcement Learning in many financial tasks that until recently were considered "mission impossible". This speed up is dictated by the maturity of the pipeline technology: cloud technologies, availability of large-scale labeled data sets, AI algorithmic libraries of pre-trained AI modules, large-scale supportive algorithms, NO-CODE platforms which allow users without specific knowledge to design AI solutions, and multiple types of easily accessible infrastructures able to support and deploy large-scale AI models. Today, AI Financial plugins helping selective tasks of the investment pipeline have already started to emerge and have had a very positive impact. Therefore it is natural to expect that in the near future, we will see a vertiginous growth of AI-Powered Investment Decision Support Systems. In conclusion, it is reasonable to predict that during the period of AI Fast Transformation and AI Financial Disruption, hundreds of thousands of Private Investors and Investment Professionals Specialists worldwide will be helped by these systems and plugins in their investment decision-making.



\Fig 4 : AI-Based Decision Support Systems in Industry

10.2. Market Predictions

A recent study projects a cumulative market for deep learning software applications, such as AI investment systems, to reach USD 118 billion by 2025, driven by vertical market use cases across multiple industry sectors. An additional USD 125 billion will be spent on deep learning hardware, with the most significant being graphics processing units and application-specific integrated circuits. The rest will be for storage and memory. Company intent to deploy deep learning is substantial, and an increasing number of use cases are being adopted across a wide range of applications. Deep learning systems (used in conjunction with big data algorithms and business analytics) will dominate the market, used widely for artificial perception applications (such as visual recognition, language processing, speech recognition), for data and business analytics, and for artificial intelligence-enhanced business applications.

According to a recent analysis carried out by an international research company that has special expertise in investment-related applications, AI and related technologies will only account for about five percent of all investments in Europe in 2024, amounting to over EUR 11 million, but companies expect that, in the long term, those technologies will have a much bigger impact. Around 17 percent of the companies see AI influencing their company value significantly by 2030. However, they believe measurable impacts will only be achieved after 2024. On the other hand, despite all the promising predictions, the actual utilization of investment management-related applications appears to be years away. It is true that the overall investment industry is going through some changes brought about by the introduction of advanced technologies such as artificial intelligence algorithms. But it appears that validating these new technologies has proven a challenge.

11. Regulatory Considerations

Investment AI systems represent a new chapter in the regulation of investment advisory firms, as they apply the traditional model of regulation. However, the uniqueness of AI-powered systems will require a discussion of issues that are not currently and adequately addressed, even by the flexible regulatory system currently in place. The predominance of AI in the production processes makes considerations like the “origin” of the product dubious, if we take into account that, at least in the first years of the adoption of the use of AI systems in advisory firms, the creation of investment advisory recommendations will be a work carried out by experts in the position of confinors of the systems – just as the users of current digital advisory services steer the service provided with a profile questionnaire, but the answer relies on a complex algorithm.

We must also consider how current regulations in traditional investments and emerging financial technologies manage to address ethic and privacy concerns when humans are replaced by AI in providing financial advices; considerations mostly ignored are the differences that use AI creates in terms of security of investor data, misalignment of goals, and overgeneralization of advice. Despite some industry attempts to bring a report on how to use best practices in the development and implementation of Machine Learning in investment management, the considerations are far more extensive and should also work in collaboration with regulatory authorities to provide concrete proposals on how to build a safe world where both investment management firms and investors may leverage the blessings of AI in their daily processes and lives.

12. User Experience and Interface Design

User experience (UX) concerns the totality of an entity's interaction chain and is the product of the availability, functionality, usability, and aesthetics of that entity. It is increasingly used in a broad spectrum of technical tools that connect users with underlying engines of complexity and power to facilitate the navigation of their increasingly intelligent and interconnected digital world. These tools, known by a myriad of names that include agents, interfaces, and systems, can be accessed through a myriad of modalities including voice, screen, and haptic. The core goal of UX is to extract the rich complexity of the underlying tools and create multiple routes for users to connect with them, augmenting their value by rendering properties of interest more easily discoverable and enhancing usability via appropriate presentation modes.

For those invested in UX work, the process of creating and refining UX is effectively akin to the creative and qualitative exercise of other disciplines such as artists, musicians, and designers in their various domains. Given the importance of UX and the unique collaborative requirements of investment decision support systems, the creation of effective UX is normally a joint effort between key teams at user organizations and the development organization. Firstly, functional requirements at user organizations need to be mined and translated into workflows that facilitate the desired underlying complex interactions between users and specific capabilities of the decision support and broader investment processes. Secondly, the explorative nature of the investment process requires flexibility in presentation with capabilities for live tracking, stakeholder curation, and the customization of views.

Thirdly, for investees or for quantitative epochs where the majority of view time is used for data exploration, the creation of effective presentations is a qualitative UX task at which stakeholders at investment firms should excel. Finally, tools, material, or information should be rendered available to enhance their contribution, considering the appropriate modality for engagement. With carefully chosen tools, external support can enhance knowledge sharing, boost accessibility, and increase engagement in decision-making for collective decisions.

12.1. Importance of UX in Investment Tools

The user experience (UX) and interface design are crucial parts of a computer tool capable of making complex decisions. Users may engage in interactive sessions with the tool and are expected to examine the results, understand the advice provided, and make their own investment decisions, but may become confused or feel overwhelmed if the interface is overloaded with information or lacks clear organization. A good UX is even more important for investment decision support systems (IDSS) than for general-purpose systems, as investment professionals are frequently under high pressure and stress when making investment decisions and may be subject to large financial rewards or penalties. Furthermore, a good investment process should be understandable and acceptable not just for the user of the tool, but also for other stakeholders. A particular risk of incomplete or undesirable explainability is the occurrence of feedback loops in the methodology or application of the IDSS. AI-based IDSS can be used to push the investment process further in the direction of fully automated trading, where beneficial short-term effects can only be generated by being able to trade many times each day. In general, a tool is preferred to a black box solution that gives a simple financial judgment on a specific investment target. In addition to professional asset managers using quantitative techniques for their clients, the investor base also includes institutions such as pension funds, family offices, corporate treasuries or central banks, but also retail investors.

One way of parameterizing the UX design is to allow the user to define clearly how much transparency they require, i.e. which parameter weights or explanatory rules are available to the tool and which activities of the strategy have to and which may not be subject to further changes.

12.2. Best Practices

Regardless of the user classes targeting functions -- from advisors, funds managers to retail -- the main objective is making investing tools more approachable. From a usability viewpoint, some best practices include avoiding wordiness and jargon at all costs. Information architecture should be chosen so the user grasps the primary functions at first glance and can intuitively navigate through auxiliary secondary functions. In addition, investing is especially prone to cognitive overload, meaning the users are bombarded with competing important bits of information - charts, tables and news. Distractors should be avoided and visual hierarchy must be carefully set.

Furthermore, advisors and portfolio managers work hard to acquire their clients and demand respect for their work and privacy. Cognitive fatigue results when people switch tasks too often or lose their focus because of environmental distractions. Since these professionals use sophisticated tools, investing too much on UX endeavours creates the tendency to "dumb it down." Retaining a certain level of technicality for power users generates a feeling of being catered for at equal foot. Nonetheless, the investment designer must sit in the user's seat. Crafting a UX so enjoyable that users talk about your product is an additional facet of the investment toolkit. Working across disciplines, at the core of the best tools to support investment decisions is a discerning creation and combination of small visual details. Creating the visible subtle details requires refining. Once the product is in use, tasks become repetitive but innovation through subtle change will make the product stand apart.

It should be also noted that in our search for the best UX, we should not forget that development budgets are short, which entails prioritizing functionalities present in most of the leading investment tools. A feature-inversion analysis to identify functionalities missing will help visualizing the actions and actual information the users of the old and future tools deem important. First deploy the most basic investment IDSS with bare tracking functionalities and add up the features to speed up the processes or make interesting forecasts or analyses.

13. Performance Measurement and Evaluation

It is essential to define some key indicators, which can measure the investment performance of the system and give a good feedback for the end users. Although the final idea of any AI-Powered Investment Decision Support System is to maximize the investment performance, the entire investment process can be split into several observations and it is worthwhile to monitor the indicators. The main key performance indicators (KPIs) can include, but are not limited to: Total Return, Annualized Return, Annualized Volatility, Maximum Drawdown, Drawdown Duration, Daily VaR, Daily Expected Shortfall. Depending on the investment strategy, other risk-adjusted indicators might also be computed: Sharpe Ratio, Sortino Ratio, Calmar Ratio, Omega Ratio, or Chestnut Ratio.

Performance measurement must be completed together with the evaluation of the message itself. Considering the uncertainty of the predictions from various models and systems, different weighting schemes can be applied to different models. Model weighting can be determined through Backtesting, on the history of data prior to the observable estimation period. When the forecasts are aggregated, they are not simply combined in the equal form. Each forecast is weighted by its forecasting accuracy and by how uncertain it is, as measured by the predicted length of its confidence interval. However,

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overconfidence of different models could weaken the reliability of model predictions, which must also be carefully monitored, perhaps by using variance in estimated accuracy. In the presence of Markov-Switching Dynamics, model weights would also be Time-Varying, 'switching' between states of greater and lesser predictive accuracy.

13.1. Key Performance Indicators

A significant body of research effort in AI/ML is devoted to measurement and evaluation, not of the not yet developed systems but of the algorithms that will be the building blocks of these future applications. In entrepreneurial decision support much innovation is in the integration of the components of these algorithmic innovations into an application. The system performance in this case is likely governed by many components, and therefore interest in specific building blocks in this area can be quite specialized. For example, there is a large corpus of work on prediction markets, focusing on data screening and prediction accuracy. There is specific investigation into the overall prediction accuracy as a measure of predictive performance for information extraction systems, and a similar focus on prediction accuracy in surveys on the prediction of cybersecurity incidents using machine learning. Examination of positive incentive mechanisms as potential solutions for improving user participation, and exploration of the model selection problem for deep learning models are also relevant.

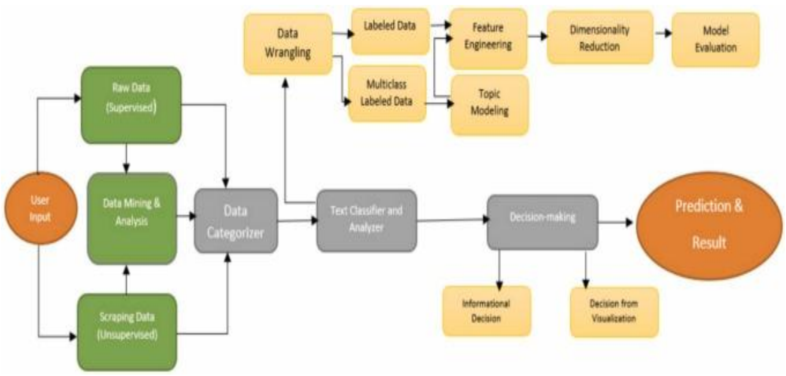

Fig 5 : AI-Based Decision Support

For any autonomous decision support system, there are two aspects of performance to consider. The first is the overall predictive performance with respect to a predefined outcome and how this outcome co-varies with performance. The second is how this performance changes on the path to this performance. Are there simpler models that allow one to get the goal of the system at lower effort levels? Are these predictors likely to change in the near future - allowing one to defer efforts to incorporate a predictor?

13.2. Feedback Loops

Feedback loops in behavioral decision-making consist of systems where individuals obtain feedback from their past behavior and use this feedback to influence their future choices. Poor previous choices create negative feedback which decreases their chances of being repeated in the future and increases the probability of different choices. Positive feedback increases the chance of repeating previous choices. Financial outcomes depend on the decisions that led to the outcomes, feedback from outcomes influences future decisions, thus influencing future outcomes, and so forth. Such a process can create cycles of feedback, positive and negative. Feedback loops primarily occur on the level of the individual decision-maker, and we find that decision support systems can help in avoiding repeated mistakes. However, they are critically important in high-dimensional environments with a large number of co-dependent agents such as financial markets.
Do feedback loops influence the outcome of investment decision support systems? Market bubbles and crashes are the typical outcomes of financial markets with feedback loops. There is no precise mathematical structure which associates bubbles and crashes with feedback systems. However, bubbles and crashes typically occur around extremes of decision variables set by the agents, when such variables are very high or very low relative to their recent moving averages. Therefore, many phenomena observed in markets around price extremes seem to be related to feedback. The influence of feedback cycles on these processes has been predominantly assumed from stylized features of market processes, such as the stochastic process generating price paths, cannot fully identify the feedback loop implications of these stylized facts.

14. Collaboration between AI and Human Decision Makers

AI has recently transformed many fields, especially those that rely heavily on vast amounts of data with associated statistical modeling. However, there are still many areas where human expertise is needed for successful decision-making.

In the case of investing, a great deal of expertise is required to avoid the common pitfalls of behavioral biases and cognitive limitations. The mounting evidence over the last several decades suggests that human decision-makers are slow, have limited attention spans, and act on the spur of the moment without adequate thought or consideration. This type of behavior could be generally classified as being too fast, as this sentiment is the essence of the rational investor theory over an appropriate time horizon.

The advent of AI and machine learning has had a great deal of importance for analysts and portfolio managers in their work processes. AI/ML is used for simpler classification or regression tasks and for building macro predictive models and then econometric programming systems that automate the econometric modeling tasks typically shouldered by economists. However, there has been much less adoption of AI-based support systems for analysts and portfolio managers to help them doing what they do best – build and utilize their own valuation and return models, perform their qualitative research and analyses, build scenarios, utilize their judgment and determine the most appropriate allocation for the different scenarios, and be responsible for the successful outcome of their trades.

15. Conclusion

Semi-automatic prediction of the future value of any asset is a well-known problem in quantitative finance. In recent years, the application of advanced machine-learning techniques to the prediction of the equity market direction, at least in the short term, has been a very active area of research. Robust predictive models trained on the decision-making history of experts, augmented by market psychology features which measure the sentiment on the market using natural language processing of technical analysis and news, constitute very concentrated, ID-centric, qualitative market signal alpha-factors and are shown to perform quite well in the short investment horizon. Objectively qualitative forecasting of the next step movement of the time series of daily asset returns in the direction of flow of big funds in the market or affectation of the market at the level of exchanges of the source of economic condensation will allow market participation in profits not only from professional market actors but also from small investors.

Reinforcement learning on exchange order flow data shows a bright promise of discovering non-exhaustive policies from different market actors, including makers, who react quickly to incoming orders, algorithmic wallets that default to academic market-making benchmarks, and large takers like broker-dealers and desks. Adverse selection over time persists, and stage-centric, least regrets staircase portfolios will still be in vogue for private investors going forward. However, for big fund market actors, the invention of a decentralized framework that allows convergence to market equilibrium over a short enough time interval on the asset price and return level is of strategic importance. This change in the current market incentive structure will allow for the refraining of fractal power law portfolios that cause devastating market sell-offs and booms found in capital transfer when exhausting market depth, ensuring the equilibriate on the asset beta avatars of the market trees of all investors.

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