HIGH SCHOOL EDITION
Journal of Student Research
Volume 13 Issue 4 (2024)

AI Implementation in Finance; What Business Have to Gain

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ABSTRACT

The introduction of artificial intelligence (AI) in various industrial and financial fields has brought both anticipation and concern. Especially, the members of different financial institutions have conflicting thoughts regarding the usage of AI to boost their output. Their concerns are not without merit, but AI has so far proved to be more beneficial than detrimental. This manuscript serves to highlight various portions of the financial sector that are utilizing AI to varying degrees of success. From using AI to identify, analyze and even tentatively automate stock market purchases, to personalizing consumer interaction while at the same time preventing fraud, to even preparing for certain scenarios where the company or bank faces the worst, AI has seeped into the interactions of the financial sector. AI is a tool, and undoubtedly part of the future, so it is best to try to understand how it interacts in the fiscal world. As with all tools, the person who is most experienced with it and is experienced with its usage the most will reap the greatest rewards. While AI proves to be a valuable asset in enhancing financial operations, its optimal performance and reliability are significantly amplified through continuous human supervision. By seeking maximum efficiency, businesses have ensured that AI-driven decisions align with both overarching business objectives and ethical standards.

Introduction

Human history has often been bookmarked by several significant events that have affected globally Plagues, world wars, and industrial revolutions serve as some of the most profound examples, shaping the course of civilization across multiple continents. Among these, industrial revolutions stand out for their transformative impact, where technology weaved its way into the daily life of a society, and brought about lasting changes that were previously unheard of prior to that specific event.

Humanity is currently riding the 5th industrial revolution wave. The 5th industrial revolution, also called Industry 5.0, can be described as a more refined version of the 4th industrial revolution (Industry 4.0). Industry 4.0 is described as an exponential growth in computer technology and biomedical science. More specifically, artificial intelligence (AI) is no longer a concept but an assistant that is found in smartphones, and biomedical technology advancement, such as gene therapy, experienced exponential gains. Industry 5.0 is mentioned as a refined version of Industry 4.0 because it strives to incorporate the previously mentioned AI development into various industries in a coexisting manner. Technological developments have increased overall efficiency throughout various fields, but increased efficiency is for naught if its users' quality of life decreases. As such, Industry 5.0 is concerned with utilizing AI to maximize efficiency while alleviating the pressure from its users.

To easily understand the advancement of artificial intelligence (AI) in finance, it is best to start with how AI has been seemingly interwoven into our lives. The simplest instance can be seen in the search window of a browser, or the autocorrect in the phones. These devices are capable of anticipating written words, and the YouTube algorithm is known to concentrate and advertise according to the user's past selections.

The core mechanisms of the previous examples are expanded in the financial sector. Online banking is a stellar example of how online security and anticipation come together within reach. An online banking application has secure cybersecurity measures to prevent fraud in financial transactions, while also providing various advertisement programs that may suit the user's needs; these advertisements were selected from the user's application usage and monetary allocation. Additionally, businesses, ever eager to maximize their profits while minimizing their costs show positive attitudes toward using AI in their business interactions (Nathan, 2024)

Early pioneers of AI inclusion into finance have broadcasted profitable numbers from 2017 (PwC, 2017.) Some have stated that the degree to which AI can advance a particular field is ultimately tied to the company's investment in AI. The change that can occur can influence national productivity and GDP numbers. Companies in North America and China are already heavily investing in AI while Europe and other Asian markets follow closely to the two investment leaders. Some companies have already stated that they have better efficiency regarding performance (Van Roy et al. 2020).

In summary, AI in finance can be classified into three large sectors: AI in quality control, AI in fintech, and AI in analytics. There may be some overlap in the three sectors. For example, AI in customer service enhancement can be utilized in both AI in fintech and AI in personalized banking; the user interface can be tailor-made by the AI to emphasize the preferences of the user while simultaneously highlighting possible future options that the user can click when they feel curious. This manuscript will explore each of the three sectors in detail. If the situation allows for illustration, real-life examples of AI in their respective sectors will be mentioned.

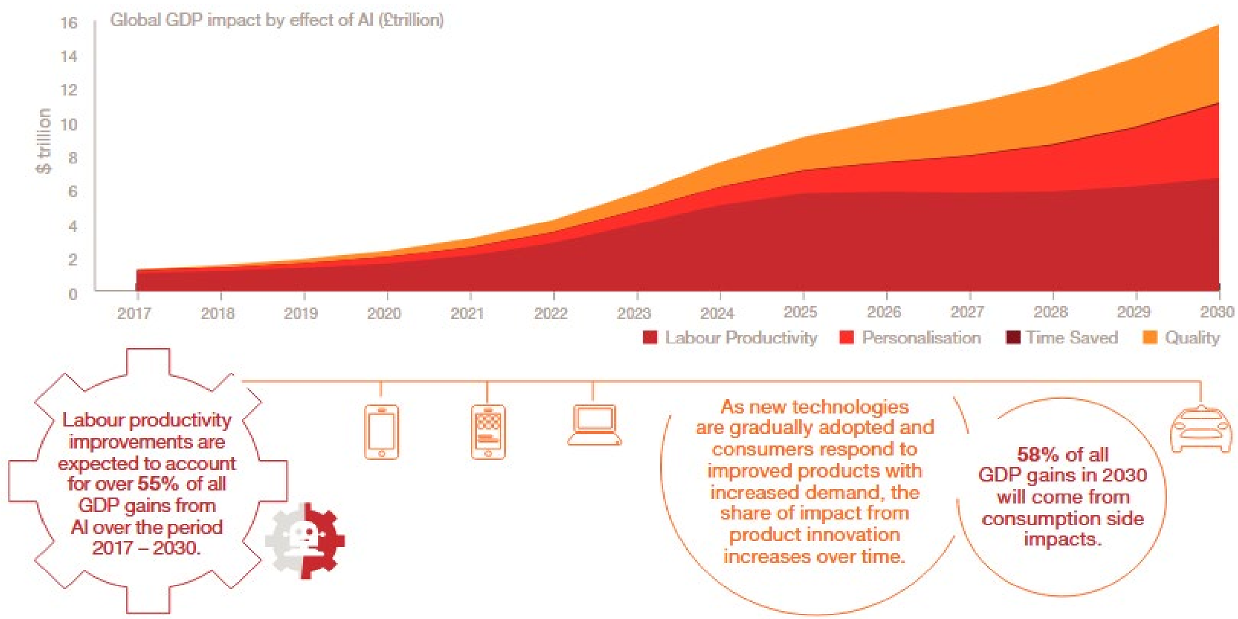

Figure 1. A profit prediction analysis conducted by Price waterhouse Coopers which illustrates the fiscal amount of profit from AI inclusion in various fields. (PwC, 2017), https://www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html

AI in Quality Control

The inclusion of AI into the traditional financial reporting sector can be thought of as a gradual trickle into an already set-in-stone environment. Although the complementary environment managed to function amiably, there were often several highlighting incidents that showed certain limits of the said system. For example, a financial report, while it is certainly detailed regarding numbers, more often than not shows the limitation of showing an overall view regarding where the numbers come from, or what implications they have for the future; other factors such as the environmental and sociological aspects of a company's workings are often abbreviated (Lupu and Ivan, 2021). A comprehensive follow-up is often invoked and such processes do injustice to the efficiency of the workings of the company.

While such inconveniences can be dwell within times of tranquility, during times of fiscal volatility they can become more than a nuisance as every decision in such times requires careful deliberation. Tangentially, sometimes upon further investigation, it appears it was these opaque non-financial factors that contributed to the instability. Such occurrences are commonplace and led to the European Union establishing a directive that states the mandatory report of such non-fiscal data (Bergmann, 2014). As such, the demand for the collection of non-fiscal data suddenly increase, and unfortunately, the companies found themselves lacking in manpower, to which they turned to artificial intelligence to tackle this problem.

Data Quality Management

Data quality management can largely be divided into three groups: 1) AI-based quality control, 2) AI risk management, and 3) fraud detection. While the first two options are relatively straightforward, the last option, fraud detection, seems better suited to AI applications in fintech, where AI serves as a bodyguard of a sort to prevent security breaches. Fraud detection in quality management is slightly different in the sense that in prevention of non-domestic inclusions into the data bank prevents the modifications of numerical values.

AI-Based Quality Control

The job description of AI-based quality control is quite transparent. The AI serves as a proofreader or number-checker to make sure the fiscal data in concern is correct. While the job description is clear, the process required to make such a proofreading AI is anything but simple. Competitive businesses have a well-intentioned tendency to identify and control all systems within their wing (Nguyen et al, 2020). They do so to identify and shore up their weaknesses while underlining their strengths in order to better utilize them. It is here, in this controlling aspect, that the aforementioned inclusion of non-financial data into the report is of utmost importance, as the information is crucial for future planning. Non-financial data can include interactions that are non-monetary in nature: product inventory, customer interaction and satisfaction, niche identification and exploitation (Nyarku and Ayekple, 2019), The importance of non-financial data depends on how it can be tied back to the financial numbers, as such companies try to connect the dots between the non-financial data and other metrics such as product or service quality, reliability, and once again delivery time (Albuhisi and Abdallah, 2018) The overall performance of a business organization cannot be properly reflected in the numbers of financial interactions, especially since matters that occur behind the money exchanging service are not properly counted toward it. This is especially apparent if the business is digitally focused, and consequently, it is important to include optimistic indicators such as service quality, product quality, time of delivery, and digital organization (Borodin et al, 2019)

Risk Management

Risk management can be thought of as accumulating and organizing information to predict the future. Although human personnel can do, and have done, such a task, the utilization of AI as a companion during data housekeeping or risk vector analysis is often a sought-after dream amongst data security organizations and teams. Additionally, by knowing which safe steps to take, a business is capable of expanding on the shoulders of educated guesses and is therefore, capable of establishing a proactive attitude in regards to future business prospects. Ultimately the purpose of AI in risk management is to minimize the risk while maximizing the profits.

One field of AI risk management is the relationship between AI and the stock market. AI-based prediction forecasts are one way how risk management can be applied to the stock market. The artificial neural network (ANN) and the central neural network (CNN) are two ways by which AI can predict the movement of money in the stock market. CNN will be talked about in detail in a different portion of the manuscript. The ANN is a relatively linear machine learning model that is successfully used to anticipate the stock market due to its efficiency in streamlining erratic changes and anticipating the next volatile movement of the stock price (Dixon 2017). More recently, a Long Short-Term Memory Network (LSTM) was suggested as an improvement to the general ANN. The LSTM is essentially an upgraded version of the ANN, and could forecast more accurate predictions in the presence of more variables in a shorter time (Zhang et al., 2021). The LSTM was suggested to function semi-agreeably in an increasingly tremulous Bitcoin market (Wang et al., 2022).

The application of the various neural networks was developed even further to automate the trading procedure. In such scenarios, the AI would conduct an initial risk assessment run, and then purchase following its readings. Such a scenario gave way to ideas of a dreaded future where all stock market transactions will be done by the AI. Bot accounts already dominate ticket offices for concerts and other festival outings, what will prevent an upgraded bot which can do the same in the stock market? Thankfully, however, such a bleak scenario has yet to manifest. Although research has been conducted in making an AI capable of automated processes since 1992, it was deemed too limited or risk-oriented to be properly deployed (Trippi and DeSieno, 1992). The most notable recent advancement of automated stock market AI requires human supervision to function properly. Although it showed notable performance in its capacity to analyze and predict the mid-price movement of high-frequency purchases (Kercheval and Zhang, 2015).

Finally, the AI and its algorithm can be used to predict and organize data of the stock market. The calculating power of the AI can accumulate and process trading information much faster than humans; AI can time the market and either purchase or sell depending on the influx of information it has access to (Frino et al., 2012). Additionally, the power of AI algorithms in stock market trading applications can be seen in their ability to reduce spreading and trade-price discovery ability; such abilities increase market liquidity, including markets with dividend announcements (Hendershott, 2011; Chatchawanwanit (2020). Indeed, although Chatchawanwanit argues that market volatility increases sometimes as more players introduce algorithm stock market analysis, others point out that algorithm stock market analysis more often than not contributes to stabilizing the market, increasing the transaction efficiency and reducing the diversification volatility in the stock market (Kelejian and Mukerji, 2016).

Fraud Detection

With the rise in mobile commerce and the Internet of Things (IoT), financial fraud has become more prevalent. To counteract these threats, a variety of advanced learning methods and algorithms have been employed for data analysis and anomaly detection (Wang, 2010). Supervised learning models, unsupervised learning methods, artificial neural networks, and collaborative schemes were used in identifying and preventing fraudulent activities. While Random Forests and Gradient Boosting Machines are among the most famous and widely used algorithms for fraud detection, the choice of algorithm often depends on the specific characteristics of the dataset, the nature of the fraud, and the computational resources available. Each algorithm has its strengths and can be effective when appropriately tuned and applied (Xuan et al., 2018; Xu et al., 2023).

AI-driven behavioral analytics can identify unusual patterns or deviations from typical behavior, such as atypical spending, sudden changes in transaction frequency, or anomalous login attempts. It can handle non-traditional data sources and detect fraud patterns that are not captured in textual data. These advanced algorithms can involve spotting suspicious transactions in real-time, detecting counterfeit documents, or recognizing unauthorized access attempts, thereby enhancing the overall accuracy and robustness of fraud detection systems.

AI in Fintech (Money Management)

The application of AI in supporting the financial sector was the main interest in the previous section, its application in company-based financial interaction is where AI is allowed to function in accordance with its programming caliber. AI in Fintech is entrenched in multiple fields that work together to both protect and enrich the user. For example, regarding security, AI can be utilized in fraud detection, as can be seen in the image below, or it can be used as a guardian to prevent access from rogue users or outside hackers.

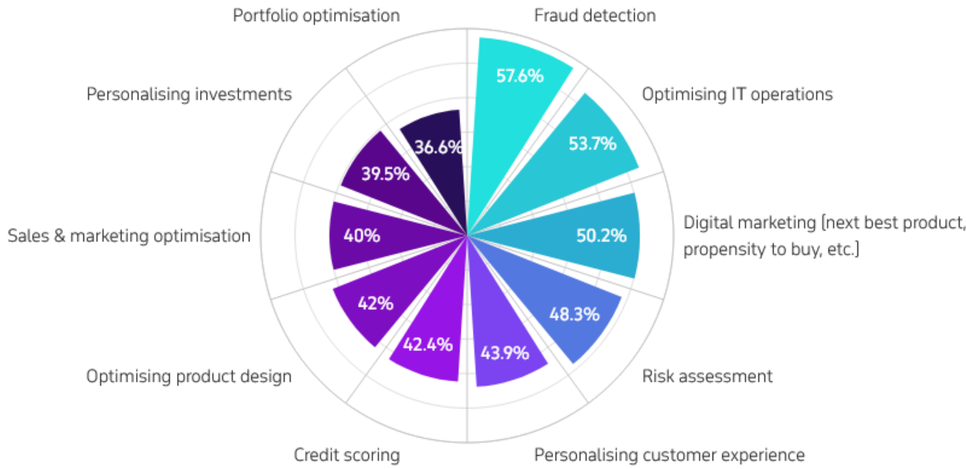

Figure 2. An example of how fintech can be utilized in multiple fields. Resource allocation may differ depending on company policy. (Ahramovich, 2023) https://www.itransition.com/ai/fintech

Compliance Monitoring:

AI-enabled quality control can assist businesses in monitoring and ensuring compliance with regulatory requirements and industry standards. By automating compliance checks and audits, businesses can reduce the risk of non-compliance, avoid penalties, and maintain a reputation for ethical and responsible operations.

AI as a Trading Model

Neural networks and machine learning algorithms are used to build intelligent automated trading systems. To give some examples, Creamer and Freund (2010) create a machine learning-based model that analyzes stock price series and then selects the best-performing assets by suggesting a short or long position. The model is also equipped with a risk management overlayer preventing the transaction when the trading strategy is not profitable. Similarly, Creamer (2012) uses the above-mentioned logic in high-frequency future trading: the model selects the most profitable and less risky futures by sending a long or short recommendation. To construct an efficient trading model, Trippi and DeSieno (1992) combine several neural networks into a single decision rule system that outperforms the single neural networks; Kercheval and Zhang (2015) use a supervised learning method (i.e. multi-class SVM) that automatically predicts mid-price movements in high-frequency limit order books by classifying them in low-stationary-up; these predictions are embedded in trading strategies and yield positive payoffs with controlled risk.

Natural Language Processing

Natural Language Processing (NLP) is a critical area of AI that focuses on the interaction between computers and human language. It involves the development of algorithms and models that allow machines to understand, interpret, and generate human language in a way that is both meaningful and contextually relevant. In the financial technology (fintech) sector, NLP is used for a variety of applications including sentiment analysis, automated customer support, and financial document processing (Oyewole et al, 2024). By enabling machines to understand, interpret, and generate human language, NLP enhances customer interactions and improves the efficiency of financial services.

In essence, the NLP can enhance customer service by analyzing customer interactions and identifying areas for improvement. By leveraging natural language processing and sentiment analysis, businesses can understand customer feedback, resolve issues promptly, and provide personalized and proactive support, leading to increased customer satisfaction and loyalty.

Figure 3. A simplified version of natural language processing in finance. softengi. (2024.). https://softengi.com/blog/nlp-use-cases-in-finance/

Chatbots in Fintech

While traditional chatbot architectures relied on simple rule-based systems and statistical methods, modern AI-powered chatbots using advanced NLP techniques have transformed these systems into powerful tools for enhancing customer experiences in the banking sector. Neural network models are trained on extensive datasets to generate responses that are both relevant and grammatically correct. A significant advancement in conversational modeling is the recurrent neural network (RNN) encoder-decoder model, also known as the sequence-to-sequence (seq2seq) model, introduced by Cho et al. (2014). This model improves the generation of responses by computing the most likely reply to a given input based on a scoring function, thereby producing more accurate and contextually appropriate replies from the dataset. To address some of the limitations of the seq2seq model, (Vaswani et al. 2017) introduced the Transformer encoder-decoder model, which uses self-attention mechanisms to better capture dependencies and relationships in the data. Furthermore, the integration of natural language models and deep learning techniques such as the Generative Pre-training Transformer (GPT), has allowed chatbots to manage and respond to customer queries with remarkable precision, setting new standards in the fintech industry (Bellegarda, 2004; Melis et al., 2017; Kushwaha and Kar, 2021).

AI-powered chatbots utilize these advanced technologies to offer a conversational interface, enabling natural language interactions between financial institutions and their customers. According to research by Dwivedi et al. (2023) and Varma et al. (2022), these modern chatbots have greatly enhanced customer satisfaction by delivering personalized and real-time services (Kshetri et al. 2024). The ongoing development and adoption of AI-driven chatbots are expected to further shape the future of finance. By continuously enhancing their capabilities, these chatbots will play a pivotal role in defining customer interactions and service standards in the financial sector.

Speech Recognition
AI-based speech recognition and synthesis technologies have revolutionized the way spoken language is processed and generated. Speech recognition (SR), or automatic speech recognition (ASR), converts spoken language into text using advanced deep learning models. Early ASR systems utilized end-to-end automatic speech recognition (E2E-ASR) frameworks, which employed sequence-to-sequence (seq2seq) models (Graves and Jaitly, 2014; Chan et al., 2016). These models consist of an encoder that processes acoustic features from the audio input and a decoder that outputs the corresponding linguistic information. The seq2seq approach simplifies the training process and enhances recognition accuracy by directly mapping acoustic signals to text. Additionally, modern SR techniques are adept at handling variations in accents and context-dependent phrases, improving their robustness and adaptability. The Structured State Space Model (S4) is another significant advancement, offering the benefits of recurrent neural networks (RNNs) in autoregressive generation without the need for masking, thus optimizing memory usage during inference compared to traditional Transformer models. These advancements are important for fintech applications where accurate and efficient voice processing is essential for tasks like automated customer support and voice-activated transactions.

Speech Synthesis
Speech synthesis or text-to-speech (TTS) technology generates spoken language from written text, creating synthetic speech that closely resembles natural human voice. The latest innovations in TTS include models like VALL-E (Wang, 2023), which excels in producing high-fidelity, emotionally expressive speech with minimal training data. VoxtLM (Voice-text Language Model) further advances the field by integrating voice and text processing into a unified framework, enhancing both the quality and versatility of speech generation (Maiti, 2024). This model leverages large-scale pre-training and few-shot learning to generate natural-sounding and contextually accurate speech, catering to various applications from virtual assistants to personalized voice profiles. These can be employed to improve customer engagement by providing spoken summaries of financial information and streamlining interactions.

Image Recognition

Computer vision technologies, particularly image recognition, are increasingly integral to financial services, enhancing security, automating processes, and improving user experiences. One of the most notable frameworks is You Only Look Once (YOLO) (Redmon and Farhadi, 2015). YOLO has stood out for its impressive balance of speed and accuracy in object detection. The YOLO framework has evolved significantly with the latest YOLOv8, incorporating advancements with techniques such as the R-CNN(Region-based Convolutional Neural Networks) and Fast R-CNN and Faster R-CNN to advance the accuracy of object detection (Girshick et al., 2014; Girshick, 2015; Ren et al., 2017; Reis et al., 2023). By leveraging sophisticated algorithms and machine learning, precise and rapid identification of objects in images can be employed. This capability is crucial in the financial industry, facilitating more informed decisions and simplifying operations.

AI in Analytics

AI in analytics is where the previous two sections converge and overlap. The data analysis method of the ANN and machine learning are applied to the financial sector in earnest. The AI up till this point had mainly been in understanding and learning about either its function in the stock market or the human interaction with various fintech applications. In this portion of the manuscript, AI is introduced in matters of material significance, such as bank risk assessment and shareholder anticipation, two fields where AI has previously shown lackluster results due to substantial human interaction.

AI and Banks

As stated before, AI, machine learning, and its products which include the various neural networks such as the ANN have been known to sometimes outperform statistical analysis done by human personnel, while also sometimes failing in such a spectacular manner that it eventually required human guidance. However, this is not a detriment, but rather it proposes an outing where human interaction and AI organization may flourish. An instance of human and AI teamwork which showed favorable results utilized the multiple-layer perceptron capabilities of the AI with logistic regression to overcome what was deemed a chink in the armor (Durango-Gutiérrez et al., 2021). More recently, banks have aggressively deployed AI in order to prevent their doomsday scenario. The personalized financial decision support systems used by a number of banks all have their roots in machine learning models (Abedin et al., 2019). Ironically the personalization of information for better security was greeted more warmly by the banks themselves than the users of the banks.

To protect the banks' best interests, the banks use various AI models, such as the previously mentioned forest model to prevent fraud. In this scenario, the human user uses the AI to identify potential credit risks. The AI models in question are the support vector machine model and the random forest model, and both have their basis in data mining (Lahmiri, 2016; Butaru et al., 2016) The result of the deployment of such models is significant and has been reported to have saved up to 25% in cost (Khandani et al., 2010).

The diversity of the random forest model in its usage as a fraud watchdog cannot be understated. The random forest model serves a dual purpose as a credit card fraud prevention system and as a credit rating change prediction device. By tinkering with the random forest model to show a degree of resistance to unwanted variables such as unidentified variables, missing variables, and extreme variables, the random forest model is capable of functioning as a sturdy workhorse that focuses intensely on important data inputs while ignoring miscellaneous signals (Xu et al., 2018). More advanced versions of forest models analyze the financial spending pattern of the user and flag him or her as a potential financial risk.

As stated in section 2.1, non-fiscal variables, often abbreviated or outright erased in fiscal reports, are significant indicators of a financial institution’s performance rating. Text analysis AI suggested variables such as regulation, organization, and management strategy as an important group that can function as an indicator of a bank’s performance (Wei et al., 2019). Other neural network AI studies also suggest that negative costs, regulatory barriers such as domestic protection against international institutions, and even cultural aspects indicate high-risk banks (Wanke et al., 2016).

AI and Corporates

Corporate identity and AI inclusion always follow the same pattern of maximizing profits while minimizing costs and risks. Up until now, most of the information was focused on maximizing profits. Herein, AI will be used to predict business bankruptcy. One of the main variables the AI uses to predict the possibility of corporate bankruptcy is by analyzing the composite financial index. Traditional linear models, although they serve their purpose, cannot properly identify and incorporate a significant amount of information into their calculation. AI-based classifiers (Sabău Popa et al., 2021). However, data-based results are not only number-focused. By combining image capture technology and risk assessment readings, various groups have interesting results. An experiment using image capture technology for risk assessment was conducted by Kamiya et al. (2018). In this experiment, it was found that masculine facial characteristics, and a certain facial width-to-height ratio, were highlighted as indicators of corporate risk in a number of data-based results. Other research groups which have manually analyzed the facial width-to-height ratio, have identified this specific facial structure with aggression and emotional volatility. Sometimes this volatility would yield positive results in a corporation's annual fiscal reports, but the same volatility backfired quite considerably due to its idiosyncratic nature. (Keck and Tang, 2013; Ahmed et al., 2018). Additionally, a separate visual analysis states that facial masculinity and fraud have a positive correlation (Park et al., 2022). When other facial feature analysis studies show similar results, the image-based risk assessment by the AI proved to be a successful implementation of AI for risk assessment.

In other corporate fields, both supervised machine learning and ANN were identified to outperform traditional linear models in cost, time spent, and accuracy. In real estate investing profit forecasting, AI considered multiple variables such as the REIT index, the lending rate, and the industrial production index to successfully predict favorable results.

Discussion

A significant amount of information was introduced in regard to AI implementation in various financial fields. As stated before, AI is but a tool that can be harnessed to successfully predict amiable results. Depending on how the AI algorithm and subsequent machine learning sequence are initially established, results will vary. So how will AI be implemented on a macroscale?

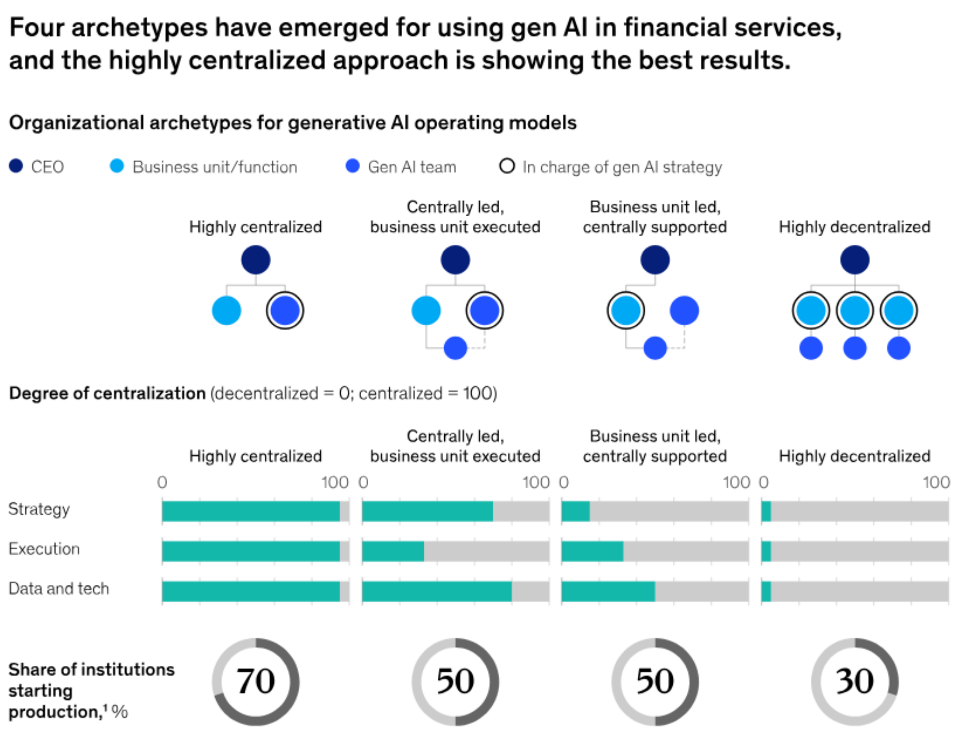

Figure 4. Various operating modules that point out the various ways AI can interact within the financial sector, especially businesses, as proposed by Mckinsey and Company (Buehler et al., 2024) https://www.mckinsey.com/industries/financial-services/our-insights/scaling-gen-ai-in-banking-choosing-the-best-operating-model

AI implementation will ultimately depend on the business type. If the AI implemented does not work well with the human resource infrastructure of the company, the company will not be able to make significant gains toward revenue production. Indeed, the cost of projecting a higher-class AI may eat up the company coffers at a rate that eclipses its filling-up rate. However, this also means that a proper AI will help the company generate profits. If there are tech-savvy personnel in the information department, especially professionals who are familiar with the AI implemented by the company, the reward-to-risk factor will only go up. While fully automated AI may appear in the future, at the moment, supervised AI implementation yields the best results.

Acknowledgments

I would like to thank my advisor for the valuable insight provided to me on this topic.

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Agarwal et al. (2022) delve into the innovations brought about by AI in finance, examining the practical applications and effects of financial intelligence from fundamental operations to risk management. Their study showcases a financial
robot in action, illustrating the tangible benefits AI brings to the financial sector, including enhanced intelli gent processing and data analytics capabilities.

Tyagi et al. (2022) conduct a comparative analysis of AI and its powered technologies in finance, emphasizing the critical role fintech companies play in enabling financial institutions to adopt innovative products and services. This research highlights the necessity for banks and financial organizations to integrate AI into their business strategies to maintain a competitive edge in today's digital economy.