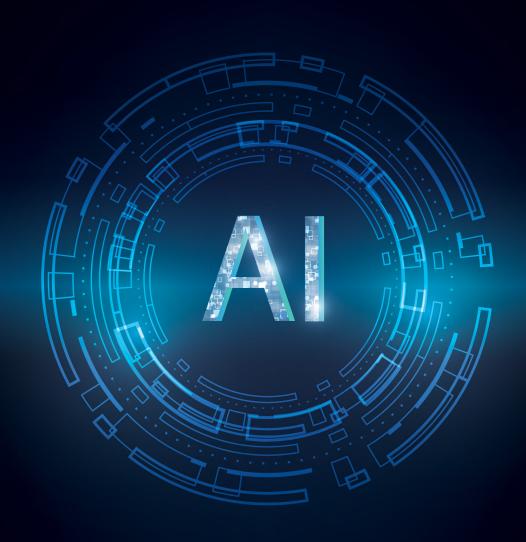
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Artificial intelligence in post-trade processing



Post-trade processing has seen frequent changes across asset classes and the regulatory landscape. These changes, coupled with human-driven decisions across processes, introduce inefficiencies and lead to errors. Artificial intelligence can play an important role in reducing these inefficiencies by easing decisioning through automated self-learning.

\$17—\$24 Bn

Current industry spends in trade processing and related functions¹

\$3 Bn

Costs and losses arising out of just 2% trade failure rate²

\$342 Bn

Cumulative fines on banks from noncompliance between 2009 and 2017³

What if?



You could predict and reduce anomalies related to trades, margins, and payments early on in their life cycle.



You could flag potentially fraudulent counterparty activities to avoid regulatory interventions and fines.



You could reduce manual interventions, increase efficiencies, and create capacity to delivery value to clients.



You could dynamically manage collateral requests based on recent market news about creditworthiness of a client.

ns, and

intelligence can help you meet your aspirations.

Artificial

Throughout the past few years, capital market firms have undertaken several initiatives in front-office operations as market participants try to remain competitive. However, post-trade operations are still supported through legacy systems leading to a multitude of challenges across business operations. Market volumes witnessed a sharp spike in 2020 with the average daily volume of matched shares increasing from 1.1 billion in 2019 to 1.7 billion in 2020 and the average daily volume of options and futures contracts increasing from 7.6 million in 2019 to 10.3 million in 2020⁴, furthering the stress on post-trade operations consisting of trade processing, position management, settlements, and risk and compliance. Concurrently, the post-trade landscape is continuously changing, introducing several challenges such as rising costs and margin pressures, higher risk and compliance requirements, and increased regulatory interventions. While large transformation programs are required to address all these challenges, leveraging cutting-edge technologies such as artificial intelligence (AI) within pockets of the post-trade processing landscape can help firms secure quick wins and enhance operations.

Challenges



Rising cost and margin pressure



Higher risk and compliance requirements



Increased regulatory interventions

An all-source analyst who has the support of Al-enabled decision support systems could save as much as **364 hours** or **approximately 45 working days a year**, a **17.5% time saving** and significant operational efficiency⁵

Artificial intelligence in post-trade processing

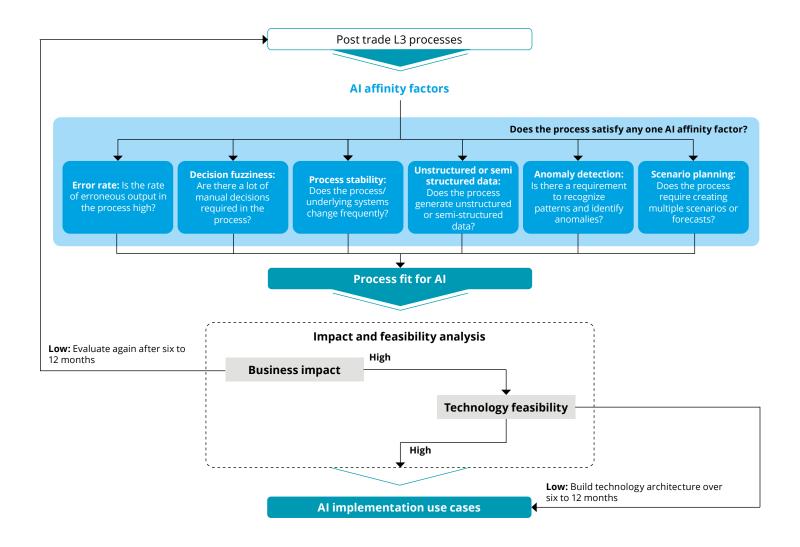
Al supports the analysis of structured and unstructured data (voice, images, text, etc.), much like a human brain, at a scale that is wider than what traditional statistical and software programs can support. Further, Al offers learning capabilities that can learn from past patterns without the need for human intervention. These capabilities, when firms effectively employ them, can significantly reduce the requirement for manual interventions, reduce reconciliation requirements, support straight-through processing, and enhance operations considerably.

In our experience, capital market firms have mainly undertaken initiatives within the realm of intelligent automation, which focuses on process automation with an overlay of cognitive technologies, but they have missed out on embracing pure Al capabilities that involve statistical algorithms to analyze high-volume data, recognize underlying patterns, and automate or enhance decision-making within their post-trade processes. While intelligent automation increases operational efficiencies, it is imperative that firms actively consider implementing Al tools within their post-trade processes to address challenges and gain a competitive edge. In this paper, we outline a framework that will help firms choose use cases for Al implementation, highlight two successful case studies of how firms have enhanced their post-trade operations by leveraging Al, and provide guidance on how firms should get started with Al within their post-trade landscape.



Al application framework

Organizations may be tempted to force-fit Al across all the post-trade processes. However, Al cannot and should not be treated as a solution to all challenges. The underlying challenges, potential business impact, asset classes, current processes and technology readiness play an important role in efficacy and acceptance of Al model within an organization. Selecting an incorrect use case for Al within post-trade processing can quickly make stakeholders lose confidence in Al initiatives. A clear answer to "how will we implement Al?" can help organizations navigating the Al journey efficiently and a structured analysis to identify and prioritize use cases for Al implementation helps in answering the question. We believe that the following approach can be a starting point for organizations in their journey to implement Al within post-trade processing:



Al affinity factors

As a first step toward implementation, organizations need to apply a filter across their post-trade processes and understand if there could be a potential AI solution to their challenges. Certain factors make a process more conducive for AI analysis as compared to traditional programmatic analysis. We have identified a few factors and illustrative measures that can guide organizations in assessing their processes and the fitment for AI. Every organization will need to customize these factors by determining additional measures and thresholds, which can help in shortlisting use cases.

| Factors | Rationale | Illustrative measures | Post-trade example | |
|-----------------------|--|---|--|--|
| Error rate | Processes with high degree of errors increases the operational and regulatory risk of the organization. | Number of regulatory rejects/errors in the past year | Trade mismatch Settlement failure Allocation Error | |
| | Al models through supervised and unsupervised learning can be used to predict error occurrences in future through anomaly detection. | Number of reconciliation breaks/errors in process | | |
| | Al algorithms can also help in automated root- cause analysis based on historical and real-time data. | Number of tickets Average rate of false positive and negatives generated | | |
| | Processes that are more prone to erroneous output can be improved through AI intervention. | Series acce | | |
| Decision fuzziness | Increased human intervention for decision- making leads to an increase in operational inefficiencies of a process. | Number of FTEs involved in the process | Regulatory violations of trades | |
| | Human intervention can help in visual object recognition, speech recognition and production, basic natural language prediction, and comprehension. | Number of approvals within workflow Number of breaks for manual intervention | | |
| | Through analysis, AI can help by identifying underlying patterns and building rule sets to undertake these fuzzy decisions. | | | |
| | As the degree of fuzziness in decision- making increases, Al can play a critical role in process improvement. | | | |
| Process stability | Process change involves changes to underlying systems or workflow. It is difficult for traditional rules-based systems to be modified based on | Number of times process or underlying systems changed in the past year | Portfolio reconciliation with counterparties for | |
| | Al can uncover key risk factors of change, predict which changes are about to fail, prevent change failure, and monitor for new threats. | Launch of newer asset classes and agreements (SWAP) | newer asset classes in OTC trades | |
| | Thus, AI can help in analyzing unstable processes (i.e., processes that change more often than others). | | | |

| Factors | Rationale | Illustrative measures | Post-trade example |
|---|--|---|--|
| Unstructured or semi- structured data | Artificial Intelligence algorithms can help in processing unstructured and semi-structured data, which cannot occur through standard statistical analysis techniques. | Number of diverse data sources | End customer issues reported via emails, social media related to margin calls, etc. |
| | | Number of nonstandard documents generated | |
| | Al algorithms help in establishing link between structured data and unstructured data. | Feedback and/or complaints received | |
| | As level of interpretability, relevancy, and accuracy in unstructured/semi-structured data generated by a process increases, Al suitability increases. | through email or social media | |
| Anomaly detection | Anomalies (i.e., deviation from expected behavior) requires analysis across time series or large volumes of data. Traditionally, analysts/risk managers have analyzed this data manually. | Average frequency of standing settlement instructions updates vs observed frequency | Proactive anomaly detection in standing orders Expired and/or |
| | Al algorithms can help analyze large volumes of data generated across wide time duration to establish trends, recognize patterns, and highlight deviations, if any. | • High deviation of price in invalid standing orders compared settle | invalid standing settlement instructions |
| | Thus, AI can help in analyzing processes where anomaly detection is being undertaken manually. | | |
| Scenario planning | Scenario planning requires analysis of multiple structured and unstructured variables, determining relationships between them and planning for future outcomes which are in best interest of the organization. | Collateral distribution and haircut requirements for | Collateral optimization |
| | | counterpartiesMarket volatility and peak total intraday funding | Liquidity and cash management |
| | Al models can help analyzing both structured and unstructured data, identify causation and correlation between hundreds of these variables, and generate complex outcomes that are either likely and unlikely. | obligations | |
| | Al supports analysis across multiple variables to create forecasts, thereby aiding in scenario planning. | | |

Business impact analysis

A business-heavy lens needs to be applied to each of the processes that have an AI affinity to understand the business impact in case they are leveraged for AI analysis. Within the realm of post-trade processing, the focus should be predominantly on ability of AI models to address some of the challenges outlined in the first section of this document (i.e., rising cost and margin pressure, higher risk and compliance pressure, and increased regulatory intervention). AI can help firms generate insights to drive efficiencies, automate risk management and compliance across post-trade processes, and create value. We believe that firms can analyze the business impact of the AI use case across following domains:



Enhance insights and productivity

Analyze and derive insights from a large amount of data in various formats across sources to increase productivity and efficiencies (e.g., identify trends that regularly lead to trade failure)



Increase compliance to regulations

Safeguard assets to help stay complaint, saving hefty penalties traditionally paid for being noncompliant to regulations across geographies (e.g., identify potential fraudulent transactions)



Reduce exposure to risk

Reduce exposure to risk by enabling an accelerated response across multiple capabilities like counterparty credit checks to cybersecurity (e.g., margin calls from counterparties based on news alerts)



Reduce costs and losses

Reduce losses and costs across the trading life cycle from reconciliation to settlement and reporting (e.g., reduction in cost of capital through collateral optimization)

Only processes that would have a high impact on business (by applying AI) should proceed to the next stage of analysis; processes with low business impact need to be taken off the chart. However, the ones taken off the chart should be periodically analyzed (every six to 12 months) if there has been any change in the impact AI models could have on the processes. This could be due to factors such as process change, regulatory compliance requirements, or increased errors, among others.

Technology feasibility analysis

To harness true potential of Al, financial institutions will require to make significant changes and ready themselves for implementation of the Al solutions. Al solution needs to be tightly integrated with core technological landscape and operating model to drive full value. Number of factors like maturity of data pipeline, underlying infrastructure, infrastructure elasticity, and data sufficiency need to be considered for Al solution deployment. Organizations need to analyze each of the use cases that pass through the business impact filter for their technology feasibility (i.e., the underlying technology architecture's ability within the firm to support Al analysis). Some of the factors that organizations need to consider while assessing technology feasibility are as follows:



Use cases that emerge as high technology feasibility should be taken on high priority for AI implementation, while organizations should start building the underlying technology infrastructure that will move the low technology feasibility use cases to the high feasibility zone within a six- to 12-month horizon.

Illustrative case studies: Post-trade processing to enhance operations

CASE STUDY

Reducing net asset value (NAV) exceptions and manual efforts by 77% using Al-based algorithm model⁶



Problem statement

- Significant variation was observed in NAV figures during securities pricing reconciliation daily at market close
- An analysis showed a high degree of exceptions—the majority of which were not true anomalies but required review.
- Analysts spend significant effort and time in manually reviewing 10,000 false positive reviews daily.



Solution

- An algorithm was built using historical data spanning over years. The algorithm correlated the movement of a certain stock against other securities in the bank's accounting system.
- The algorithm analyzes and reviews the daily movement of securities against the one that was expected to move up or down.
- If an anomaly occurred (e.g., a stock price moved up by 10% when it was expected to do the opposite), the tool raised a flag for an analyst to review.



Impact

- Using machine learning and predicative analysis, the AI tool was successful in reducing exceptions by 77% against hundreds of thousands of unique positions.
- ◆ The tool saves considerable manual effort and number of hours spent in investigating normal market events, such as the response to an earnings report or stock split.

CASE STUDY

Prevent trade failure by Identifying potential trades most likely to fail even before the failure occurs using an Al-based predictive analytics tool⁷



Problem statement

- Trade settlement failure is a known issue in the post-trade processing space, and the exceptional processing of a failed trade is a labor-intensive process.
- According to the DTCC, a trade settlement failure rate of just 2% may result in costs and losses of around \$3 billion.8
- The large volume of trades that fail require a high degree of human intervention to analyze the issue and provide resolution.



Solution

- A leading financial institution developed a model based on an algorithm that leveraged thousands of failed trades across varying factors.
- The model includes 100 different factors such as the time of trade, the value, the location of the counterparty, and a broker's history.
- The algorithm can identify the subset of trades that are most in danger of failing altogether, suggest the reasons why, and propose the actions needed to rescue them.



Impact

- The model accelerates the average matching time and reduce the overall number of failed trades.
- The middle office team **spends less time** on trades that are unlikely to be problematic.
- There is more transparency on trades, ultimately allowing clients to determine key risk identifiers.

Implementation planning

Challenges

Once organizations have identified use cases with high business impact and high technology feasibility, it's time for implementation. While enterprise Al adoption is accelerating at a significant growth rate, many organizations still find implementation and deployment of this technology to be daunting.

| İİ | Business case definition | Defining clear problems to make effective use of Al solutions is challenging and requires taking into considerations existing and future processes, products, and services. |
|-----|-------------------------------|--|
| | Diverse data requirements | Al solution efficiency not only depends on the volume of data that flows but also the quality which, is difficult to deliver as data is usually spread across multiple systems, sources, and varied formats. |
| | Privacy and security concerns | Protecting access to sensitive information from breach/theft as Al models require vast amounts of data to be able to make efficient decisions. |
| 000 | Integration complexity | Ability to integrate AI solutions with legacy systems, existing applications, business, and infrastructure. |
| · · | Bias decision-making | Possibility of potential bias decisions made by AI models driven by the flawed data sets that flows in the model. |
| | Legal challenges | An inaccurate/faulty algorithm coupled with inefficient or limited data can lead to incorrect decisions exposing the enterprise to legal risks. |

Implementation considerations

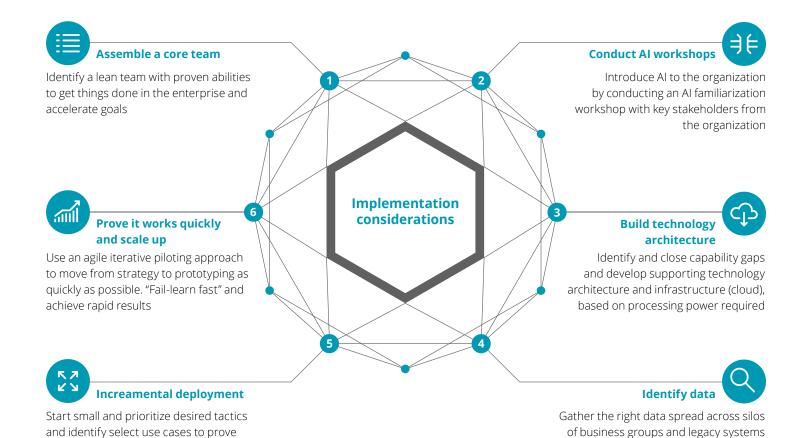
Organizations need to clearly articulate the problems, define benefits, identify right data, develop requisite skill sets, and overcome functional silos to enable AI implementation. Since organizations have limited bandwidth and budget, focused implementation planning needs to be undertaken, which will drive AI deployment and adoption. Companies should create pilot projects based on identified use cases before rolling out the solution across enterprise. This is critical in helping gain organizational confidence and overcoming initial resistance to change.

Outlined below are a few considerations that can help organizations in rolling out AI within their post-trade landscape.

According to Forbes's, only 14.6% of firms have deployed Al capabilities in production.⁹

and eliminate inconsistencies to provide

accurate data set



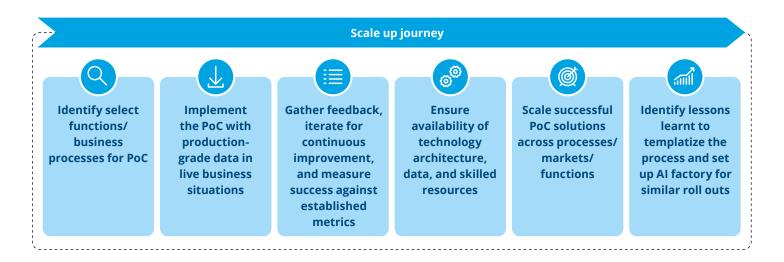
efficiency and value, gather feedback,

and expand gradually

Scaling up

Organizations should outline a detailed plan for scaling up Al solutions by ensuring enough collaboration between technology architects and business process leads. Scaling Al requires test-and-learn methodology, wherein Al models are subjected to continuous learning from the feedback gathered and refined data.

While 84% of C-suite executives know they need to scale Al across their businesses to achieve their strategic growth objectives, only 16% of them have moved beyond experimenting with Al.¹⁰



The post-trade processing space is inherently complex with varied processes across legacy systems and proliferation of data coupled with constantly changing regulatory framework. A structured approach to leverage AI as outlined in this paper can help organizations optimize these processes at scale with increased efficiencies.

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For more details on how these solutions can address your specific business challenges, contact the authors below.



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