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Artificial Intelligence and Financial Decision Making – Review of efficacy in Usage within Financial Organizations in India

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Abstract

Artificial intelligence (AI) uses statistical modeling to make predictions and in finance industry usage of Artificial Intelligence (AI) algorithms has increased several folds in recent years to detect fraud, automate trading activities, portfolio management, customer relationship management and to deliver financial advisory services to investors. Inherent ability of AI to analyze several data sets within a short span of time as well as to build alternative business scenarios to facilitate decision making helps to improve the financial performance of an organization that too without being unambiguously programmed for estimated outcomes. The research looks at the effectiveness and acceptability of AI implementation within Indian Financial Industry and the level of improvement that this integration has generated. Research Discusses some modern AI tools being utilized in the Financial Industry and tries to explore the comfort level and expectations of employees of Indian financial industry from the use of AI. It also makes an effort to statistically check the level of integration and kind of relationship that may exist between AI systems and functionalities and effectiveness that they have brought in Financial Decision Making across all sectors and players within Indian financial industry and across all levels of job positions within different financial organizations.

Keywords: Artificial Intelligence, Financial Decision Making, Financial Organizations, Machine Learning

Introduction

Artificial Intelligence (AI) with time has grown in usage and now being routinely used in every activity of financial sector to make accurate predictions. AI has become more complicated as environment is dynamic and at times situations demands sub-optimal, shortterm decisions that are necessary to enable long-term gains and successful attainment of strategic goals.

AI had long standing relationship with finance and this relationship started much earlier than the appearance of mobile banking technology, dexterous chatbots, search engines and skillful robo advisers. The extraordinary capacity, availability of precise accounts, availability of voluminous data and quantifiable, computable nature of the financial sector, makes the sector or industry (Financial Sector) better suited for the usage of Artificial Intelligence.

As on date, machine learning has started playing an essential role in several fragments of the financial ecosystem, ranging from activities like approval of loans, to computing credit scores, generating credit ratings, to more analytical and complex management of assets and liabilities (Balance-sheet analysis, especially in banking sector), and assessment of risks. Few technically-savvy financial services professionals and technocrats have showcased a very acute sense of adopting and adapting artificial intelligence into their banks and financial institutions and some has very astute but perfect view of where artificial intelligence could performance a very effective role in their companies so as to make bottom lines significantly healthy.

An intelligence framework helps to leverages Artificial Intelligence and Machine Learning or Deep Learning superpowers so as to help organizations make business and financial decisions in real time. AI facilitates the collection of information that would be needed in order to take accurate and timely decisions that too being devoiced of any sub-optimality alternatives because of paucity of time, non-availability of complete facts, or the lack of ability to swiftly access accurate data. Humans' have limited ability to comprehend and access data moreover to find out concealed dimensions of a given financial conundrum, but Artificial Intelligence has an enhanced capacity in comparison to human beings to plunge into large volume of data analysing every piece available to reach accurate financial decisions. To bring home the point, following examples would illustrate how Artificial Intelligence facilitates and adds value to financial decision making.

• To take banking to customers' doorsteps AI based research can facilitate development of an effective mobile banking application.

- To provide investors' with real time stock market data and facilitating investments decisions Applied AI is used with data analytics via mobile app that facilitates trading and builds portfolios.
- Decision intelligence has been in use for quite some time now within mobile banking applications so as to effectively meet customers' various financial needs and goals plus making switching to another service easy when needed to do something else or make active investment decisions.

Artificial Intelligence has a tendency to to be more precise in drawing insights plus generating foresights especially when a large volume of data is fed into the system. This singular characteristic facilitates the financial services industry as it have a tendency to to run into massive bulks of data pertaining to every day dealings, generation of bills, cash payments (cash flows), dealers, customers as well as third party transactions, that are perfectly being analyzed by machine learning so as to give a business insight on most profitable services to maintain in product portfolio or to bring down in size wasteful costly operations. Banks need not to deal with life-or-death scenarios like firing or facing a missile and avoiding or surviving a car crash. Using AI a bank can add value to customer's experience by informing them about available alternatives for both short-term plus long duration decision-making, especially pertaining to their daily financial choices or providing value added inputs to meet their various financing decisions ranging from monthly grocery shopping, management of commuting expenses to make sufficient provisions for buying a first house or for effectively meeting children's' education needs. AI would surely be a much treasured source or asset in the hands of a financial institution for building all these scenarios as well as for the several others.

Nowadays, many leading fintech and major financial services corporations are integrating AI and other complicated technologically advanced decision supports in their routinized processes plus procedures, consequential in an improved rationalized process that reduces risk, moreover would help in building augmented portfolios.

A machine is a machine and AI is no exception as it is also as effective as the data it has been provided with and parameters that it recognizes and has been trained upon that is where the value of human decision making besides sensibilities are being put to test. The AI could generate the seamless conclusions from the given well-thought-out, organized and systematized data but the suggested outcomes (final conclusion being offered by the system) might not every time be well aligned with extensive vision or the strategic direction of the company and may result into severe fall outs if implemented in true sense. To highlight, may be an Artificial Intelligence algorithmic process may calculate and suggest that a specific High Net worth Investor (HNI) can optimize portfolio returns if more risky stocks could be added into the portfolio and risk profile could well be adjusted to investor's life stage and may drop some of non-attractive Government debt securities. Based upon personal interactions and long experience of dealing with this HNI could suggest alternatively his preference for risk avoidance and inclination to follow a safer investment strategy. This is not a one-time issue but one of the several recurring issues that might highlight the insufficiencies of Artificial Intelligence and could suggest non replacement of Human Intellect as for some more time in critical financial decisions as on date.

Undoubtedly AI is a inordinate tool at proposing innumerable ways to attain a desired end so that financial decision makers can easily opt for or select the most optimal alternatives but AI is not a replacement of human element nor it could be used in place of human intellect not in near future at least.

With time AI got too improved and became more advanced, now it heavily depends upon entering numerous data sets so as to facilitate lightning fast generation of wide range of decisions that vary across several operational fields ranging from mortgage pre-qualifications to credit limit upgrades that too as and when called for. The large amount of data and the contracts plus the time taken to access them and manually analyse and take realistic (riskminimizing) call were actually the reasons that were dawdling the speed of banking operations weighing the financial industry down, so arrival of AI is the blessing and the amalgamation of AI in Financial Decision Making almost seems like a symbiotic relationship that was much needed impetus for the industrial growth (AI seems more like growth engine for financial industry).

Implementation of the New Model

AI and machine learning's primary power lies within innate influential and great commanding capabilities to process and successfully provide optimal solutions to highly critical issues but high level of cognizance and top management's commitment is still needed for successful implementation. Study by PricewaterhouseCoopers (2016) highlighted that most of financial organizations in United States are severely restricted by financials (available budgets), laws, and availability of resources of all sorts in successful execution of AI thereby limiting their readiness for future challenges and revenue growth.

It is not easy to bring technological transition especially introduction of AI so as to integrate and add value into complete chain of operations for example it is completely new challenge and experience to do transition for a Google neural network into relevant financial documents. Another dimension is the customer education and orientation to use AI, financial institutions have to educate and bring in level of comfort in consumers' to use AI in their daily interaction with financial institutions and Banks. Recently conducted ServiceNow survey found that several consumer-facing chatbots are comfortable using them and found the service to be more useful and helping.

AI is not only about chatbots and automated investment robos. There are several other functions that could be made more value added or efficient using AI solutions for example, a bank's call center receives thousands of call every month and these calls are regularly recorded for maintaining quality check and training purposes, only a very limited number of calls are being screened and scrutinized by the quality control department. Artificial Intelligence could very easily track plus screen these calls to find out patterns and trends amongst individual call center executives, calls made by customers, issues and concerns raised plus considerably more information could be derived, can even engender meaningful judgments from the calls as well as adding extra protection to secure customers' privacy.

Using AI and implementing technology standalone does not solve the purpose of bringing in the efficiency or generating healthy bottom lines but there is a need to bring in an effective balance between adoption of technological innovation and humans. This effective interface between humans and AI, maintenance of effective yet delicate balance could offer measurable benefits for a bank or financial institution that embraces it. Recent research conducted by Accenture highlighted that several major banks, those who invested large sums into AI and its collaboration with human beings (developing human skills) at the identical proportions or ratios as that of major global corporations have recorded near about 34% rise in revenue moreover the employee retention ratio have also registered a growth of 14%.

Adoption of AI has allowed banks to be further embedded in the daily life of a customer. This acceptance of modernistic approach to banking and acceptance of modern day technology as part of everyday operations would provide banks with the authority or ability to control financial data of the consumer so as to effectively predict consumer behavior or even to influence it. As an alternative of just accepting deposits and managing cash besides recording account balances or managing credit card debts, banks would be soon able to provide personalized recommendations concerning a customer's personal and professional goals and their financial needs based upon respective life stages and banks would also be able to guide certain clients as to the appropriate stage to request for a salary increment or enquire about much awaited promotion or the amount that could be easily spent on buying a new car.

Futuristic AI tools serves as additional set of eyes and ears in facilitating wealth managers and financial planners or investment advisers to be better contextualized with financial decisions moreover to offer educated and well-conceived recommendation at all critical junctures to their valued clients.

Recent Research studies and Mc Kinsey report (2020), showcases AI's heightened capabilities in assisting banks and financial institutions well in delivering routine as well as sophisticated financial responsibilities. Age old established organizations are meeting with aggressive opposition from novel companies that are equipped with the whole lot from cryptocurrencies and blockchain technology to crowd-funding and cloud-based computing tools. This competition is leading mercilessly to wafer thin margins that may cause serious issues for sustainability in long run; AI and machine learning could provide effective solutions that could facilitate effectively meeting competition head-on. This demands hefty investments that would offer healthy ROI in long run if implemented in word and spirit. Adoption of the modern technology decorously and in a further ascendable approach is the only resolution that would help the gigantic companies to stay in the game, important is to note that this too is not without barriers.

• Applying AI in BFSI Sector:

Very soon AI will find its means to create a robust and resilient presence in the financial industry as well to inseminate the entire financial decision making process within the industry. Given below are few examples of how AI and machine learning are being put to use in BFSI sector today. Important fact to remember is that some of these applications leverage multiple AI approaches at a go and it makes them as more complex technological initiatives. Following services uses AI and machine learning so as to provide more value added services to the clientele.

Portfolio Management

Portfolio Management is a complicated process as it involves intricate mechanism and sincere advice. AI has provided a solution called "robo-advisor" it is now trend in the financial landscape in domain of portfolio Management Services. The term is bit confusing and misleading as it does not involve any robots or any interaction of mechanical robot with human advisor. To bring the term to context a robo-advisor is an algorithm constructed to standardize a portfolio of financial products or assets based upon the objectives plus appetite for risk of the user. It also enables to continuously monitor and measure the performance of the portfolio and generate timely advises in terms of statements of performance so as to

provide insights about portfolio performance to the investors. The system attunes the portfolio in accordance to the modifications observed in the investors' objectives in addition to the variations occurring in the market so as to generate the most appropriate fitment for the attainment of investor's monetary objectives. These highly advanced algorithms, 'robo-advisors' have become really important in terms of usage and preference as they have added substantial adhesion within the segment of millennial consumers, who do not need any human advisor to guide them or to made them feel comfortable while investing as they prefer to take their well-educated investing decisions independently using the available information.

Algorithmic Trading

Algorithmic trading (originated in 1970's) also called "Automated Trading Systems," it comprises the use of complex AI systems that facilitates tremendously accurate faster trading decisions that may result in sufficient positive outcomes during even intra-day trading. Algorithmic systems facilitates making several millions of trades every day, therefore the connotation – "High Frequency Trading" (HFT) has been associated, that could be regarded as the subcategory of algorithmic trading. Maximum of the hedge funds plus several large financial institutions in terms of value and volume of trading do not discuss their Artificial Intelligence systems and techniques associated with trading or associated with strategies adopted for trading, that too for worthy reasons, it is widely assumed, that critical role is being played by machine learning and deep learning in making real-time trading decisions resulting into trade volumes and values that helps in generation of substantial returns at times even over performing markets.

Fraud Detection

Modern day computing, extreme use of cloud storage, use of cloud computing and neural networks all combined with more super computing power, have a great recipe for data security threats. The security threats in cyber space have become quite common and so are the identity and data thefts also accompanied by corporate espionage. Early financial fraud detection systems used complex sets of rules. Whereas modern fraud detection systems follows more logical and systemic approach of checklist of risk factors (cyclical and learning), as it actively generates more and more factors to be considered while providing protection plus it learns moreover calibrates itself to potential security threats.

User or customer security in banking and finance is a critical factor and has very high importance, it currently attracts huge investments making it as high stakes game both due to large level of volume of frauds, losses and investment in infrastructure so as to curtail the incidences. Other than fraud there are security risks concerning personal information, loss of

login credentials and financial scams using webpin, usernames, passwords, and security questions that takes bulk of toll for financial security issues and time. These present issues may not be considered security issues or threats for the user with reference to the safety concerns in few years from now. Over and above the latest anomaly-detection applications (random testing of back-end information based application) those at this time as being discussed are getting developed and would be soon used in fraud detection. The security measures for the future may need more high-end approaches of AI that may need the user to use facial recognition, voice recognition, or other biometric data in order to do their routinized financial transactions at a branch or even at an ATM.

• Other Areas of AI Application

Discussed above are few areas that have been either been influenced by Artificial Intelligence or have accepted Artificial Intelligence within their processes up to a great extent. Few other areas been exposed to and have adopted Artificial Intelligence within gambit of their business activities are Underwriting and Insurance, Customer Services, Retail Banking, Selling of Financial Products, Sentiment and News Analysis, Asset and Investment Management and Payments Management Systems.

Algorithmic Machines and Analytical Tools and advanced programming has all changed the underwriting game and it is expected that most of the work done by humans in underwriting would soon been taken over by machines similarly in Customer services use of chatbots and robo advisors has gained in popularity as most operators are looking forward to provide best service experience to their customers.

For the Hedge funds do hold their cards pretty close to themselves, moreover we cannot anticipate to know too much about how sentiment analysis is being used specifically for making investment (both buy and sell decisions) using Algorithms and Artificial Intelligence. Conversely, it is expected that future AI applications will be in understanding the impact of social media, news trends, and other data sources, not just stock prices and trades so as to help investors make appropriate assets and investment decisions. Machine learning might be able to imitate as well as augment human "intuition" for the financial activity by discovering latest trends decoding prominent signals.

Development of Next Best Action tools that are power-driven by AI can very accurately predict as well as make appropriate suggestions based upon customers' life stage and any changes that comes within the life stage, if a customer only just had a new born or the baby, the algorithmic changes would make the system to adjust accordingly and put forward the optimum amount to be reallocated and appropriate point in time to save for setting up for a

college reserve in addition to offers a succession of additional financial management guidelines so as to help the customer save for the needed life stage requirements and to fulfill financial objectives.

The Retail banks are also eyeing significant gains from the usage of advanced analytics, especially competition is heating up and new challenges are being stalled by digital banks in terms of efficient and highly improved competitive pricing strategies, usage of data driven product marketing and adoption of advanced segmentation and personalization. Other than enhancing customer experience and better product delivery, beyond making decisions and brining in efficiency in front end of banking operations, the AI can take care of lead scoring along with optimization of backend operations so as to make them more fine-tuned and better rewarding moreover less risky.

Literature Review

The usage and future potential of Machine Learning and Artificial Intelligence in financial decision making was, first time researched and scrutinized in **Hawley et al. (1990)** with a very specific focus on usage of neural networks as an aide to expedite and add value in financial decision-making. Resonating the future benefit of AI, especially machine learning to banking especially in the domain of credit issuance, quite a few early studies were published in the Journal of Banking & Finance throughout the 1990s. The early studies reconnoitered the potential for Machine Learning so as help in improving lending decisions and making the process of credit risk management more efficient and effective. **Altman et al. (1994)** used neural networks to classify Italian firms. Framework was constructed upon probabilities and possibilities of facing financial distress under given conditions. **Varetto (1998)** used genetic algorithms on the same topic as he used the same study to bring out his findings.

Bagheri (2014) has discussed about the ways Artificial Intelligence is reconditioning the process and procedures and the expectations people have with finance and financial industry. Artificial Intelligence is helping the fiscal diligence to get modernized and advances as well augment advancements to cover from credit approvals to measuring the effects of quantifiable transaction and outcomes of commercial risk administration and mitigation efforts. Traditional banking as we knew it and saw over the years has also transformed and so did the financial services being offered thanks to the great innovations and high end usage of technology especially Artificial Intelligence to continuously add value and similar positives have been added to the rest of the business functions.

Vijay (2019) discovered several advantages that are being generated by usage of Artificial Intelligence for the Banking Industry. Banking processes including processes of customer relationship management have been transformed by Artificial Intelligence. Immense value has been added by making several processes more value added in terms of detection of financial frauds, meeting regulatory compliance along with constant updating in regulatory requirements and evaluation of creditworthiness of loan applicants. Artificial Intelligence holds the capability to cultivate better business processes as it could offer personalized services besides helping in attainment of larger objectives such as 'financial inclusion'.

Chan, Nayler, Raman, & Baker (2019) discussed that the financial services conscientiousness has a great past dedicated to expansion of computable approaches and creating a more forward looking set of rules to upkeep and maintaining appropriate assessment processes. These set of rules and modernistic approaches formed the basis of AI synchronization within financial processes, and the industry has consequently been well-informed about AI implementation and the advantages so generated, placing AI at the lead of employing and promoting decision making capabilities within financial industry and providing cutting edge advantage of right information and much needed knowledge.

Bahrammirzaee (2010) highlighted that Artificial Intelligence can have deep impact on human intelligence by ascertaining frameworks and variability that subsists within massive combinations of data, numbers and figures, that are tremendously important in solicitations i.e. recognition of incongruity and inconsistencies (instance; false dealings). Artificial Intelligence may be able to scale, measure and program repetitious offbeat tasks and jobs in a projected procedures for scaled up performance – composed plus organized with multidimensional computations, used for building illustrations and iterations used into risk identifications associated with multilayered multi-dimensional commercial transactions having severe implications.

Kumar, Aishwaryalakshmi, and Akalya (2020) suggested that to survive and sustain in this dynamic, competitive market, in wafer thin profit conditions banks must adopt artificial intelligence and espouse moreover implement their strategy of doing a business focused upon using AI systems.

Patel (2018) discussed how Artificial intelligence has abetted and encouraged the financial sector by giving diverse services in an programmed moreover mechanized tactics as well technologically advanced offerings such as smart wallets, personalized banking services, voice assisted banking, advanced underwriting, and above all data-driven AI applications for lending purposes, plus extending best quality customer experience and support.

Kumar et. al. (2019) showcased, help and support provided by artificial intelligence in the advancement of customer satisfaction and quality of customer services being delivered by organizations adopting AI as main stay for CSR. Adoption of AI reduces frauds and increase profits, it also brings down operational costs, wasted resources, duplication of efforts and complications. The most visible evidence of the applicability of AI concepts and systems have been in extreme developments and modernization taking place in the insurance sector especially with underwriting services in terms of risk measurement and mitigation. Artificial intelligence has been proved very helpful in customization and personalization of the services and products within several industries including those in financial industry.

Patil and Kulkarni (2019) highlighted the usage and associated advantages with Chatbots and Robo Financial Advisors as they are designed in a manner to cater large number of customers in a highly cost effective fashion also being helpful in solving the gibberish and wide of the mark decisions executed by managers. Cost associated with operating a Chatbot is very low when compared to the large number of functions and operations that a Chatbot could perform. A Chatbot could handle great number of accounts in comparison to a human financial advisor. Chatbot is also the preeminent preference for investors who could not meet the expense of a financial advisor because of their demand for high fees irrespective of their inefficiencies and poor decision making abilities.

Fethi & Pasiouras (2009) critically evaluated the usage of AI in terms of AI's ability to deal with commercial services and financial services. Primary applications of Artificial Intelligence was considered as an algorithmic tradeoff, a configuration of trading portfolio and leveraging the investments, developing financial models, authentication of data and variability inherent in data, rechecking and testing of information and models so built upon the same, use of robotic-instructing, use of robo-advisors, simulated purchaser subordinates, exploratory searches for value, generating supervisory agreements and pressure trial assessments. All of the above has been attributed to the adoption of AI within business systems and infrastructure of Financial Industry so as to make the sector more efficient.

Alzaidi (2018) argued that the technological adaptation by banking sector in Middle East have been at a much slower pace especially for the introduction of AI when compared to other markets or advanced countries. After the initial resistance the Mid-Eastern markets have understood the importance of AI and off late there has been a shift in the attitude of the professionals of banking industry as they have adopted the modern tools of technology and are determined to work with AI tools and adopt development of technology as part of industry dynamism needed to sustain in competitive environment.

Two key scientific publications affecting the opinion on application of modernistic tools in investments and stock market operations were published in the year 2007 and 2008. These publications talked about applying neural networks to the technical analysis of stock prices and was contributed by **Chavarnakul and Enke (2008)**, they used a generalized regression neural network to predict from two technical indicators that combine volume and price signals, and another ground breaking work was delivered by **Tilakaratne et al. (2007)**, as the author used inter-market indicators processed and analyzed using modern technological tools and algorithms to predict future movements and market volatility and variability of returns as compared with investment horizons and associated market factors.

Dempster et al. (2001) and **Hussain et al. (2016)** have applied variations of reinforcement learning for technical analysis into their research resulting into better and advanced genetic programing later being programmed for the usage in studying technical indicators to predit stock price movements and on-off variability or short-term off-trends. **Dempster et al. (2001)** used advancements of reinforcement learning and applications of genetic programming to study and analyze technical indicators as used in Forex trading especially in terms of recalibrating relative strength and momentum oscillators being generated from different variables over large volume of time bound data.

Eletter, Yaseen, & Elrefae (2010) highlighted the daily operational aspects of the financial industry being affected by the usage of AI as AI has been applied to acquire the advantages of better informed prompt decisions, generating cost efficiencies and moreover bringing an added advantage of supported decision framework with the help of value added faster assistance.

Several authors have discussed examples and cases of leading financial corporations that have adopted AI as preferred tool of competitive advantage, implemented AI throughout organizational operations so as to attain considerable technological progression resulting in better quality functional assistance being offered to the customers, edifying performance and engendering greater financial proceeds via sources of income.

Research Data

The research primarily used primary data collected from the 215 employees of several financial institutions including Banks (both private and public sector), Insurance and Non-Banking Financial Corporations (NBFC) working at different levels of job roles and involved in varied levels of decision making. Due to pandemic situation and existence of several limiting factors restricting free travel and face to face meeting and collection of interview

data, online questionnaires were shared with selected 433 representatives out of whom 242 selected participants responded. Out of 242 respondents only 215 questionnaires were completely filled and were comprehensively covered giving clear idea about the research questions asked. Most of the questions were rated using 5 factorial scale 1 being least acceptable or favorable and 3 being neutral and 5 was most acceptable and favorable.

Sampling technique used was non probability sampling (convenient based) or more closely could be called convenience sampling as we randomly shared our questionnaires with 62.5% of the available population from the listing that was procured. Total of 242 responses received with 215 completely legitimate respondents, who were used for analytical purposes. Other details of the data are shared in Table 1 – Research and Data Collection appended below.

| Data Collection Methodology | Primary | | | |
|--------------------------------|--|------|--|--|
| Research Design | h Design Quantitative Design - Descriptive Resear (Survey Method) | | | |
| Sampling Technique | Systematic sampling technique | | | |
| Variables | Number of respondents | %age | | |
| Gender | | | | |
| Male | 101 | 47 | | |
| Female | 114 | 53 | | |
| Total | 215 | 100 | | |
| Age group | | | | |
| 18 to 30 years | 99 | 46 | | |
| 31 to 40 years | 82 | 38 | | |
| 41 to 50 years | 34 | 16 | | |
| 51 and above | 0 | 0 | | |
| Total | 215 | 100 | | |
| Occupation / Sector | | | | |
| Banking sector professionals | 37 | 17 | | |
| Insurance sector professionals | 32 | 15 | | |
| NBFC's professionals | 146 | 68 | | |
| Others | 0 | 0 | | |
| Any Other Variables | NA | NA | | |
| Total | 215 | 100 | | |
| Total | 215 | 100% | | |

TABLE 1 – RESEARCH AND DATA COLLECTION

The Analysis

The data collected has been put to test to check the Null Hypothesis – Usage of Artificial Intelligence has no role in enhancing effectiveness and efficiency in financial decision making within Financial Organizations operational within domestic frontiers of the country in India. Chi-square test, Directional Measures, Correlation, Reliability test and ANNOVA (Analysis of Variance between Variables) has been calculated.

Calculating Chi-square test

TABLE 2 - Case Processing Summary

| | | | Ca | Cases | | |
|----------------------|-------|---------|---------|---------|-------|---------|
| | Valid | | Missing | | Total | |
| | Ν | Percent | Ν | Percent | Ν | Percent |
| MLFunctions * Values | 215 | 88.84% | 27 | 11.16% | 242 | 100.0% |

TABLE 3 - Chi-Square Tests

| | Value | df | Asymp. Sig. (2-sided) | Exact Sig. (2-sided) | Exact Sig. (1-sided) |
|---------------------------------|----------------------|----|--------------------------|----------------------|----------------------|
| Pearson Chi-Square | 148.567 ^a | 1 | .000 | .000 | |
| Likelihood Ratio | 186.422 | 1 | .000 | .000 | |
| Fisher's Exact Test | | | | .000 | .000 |
| Linear-by-Linear Association | 148.053 | 1 | .000 | .000 | |
| N of Valid Cases | 215 | | | | |

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 66.50.

b. Based on 2X2 tables.

Important to note that the P-Value is < .00001. The result as could be observed is significant at p < .05.

The rows of great interest are **Pearson Chi-Square** and the footnote appended above.

- The calculated test statistic (Value of Pearson Chi-Square) is 148.567. Observed value is high.
- The footnote as seen for this statistical test showcases that the assessed cell count assumption (i.e., expected cell counts are all > 5) {all observed values are higher than5}: it also suggests that none of the cells has an estimated count less than 5, therfore what was assumed actually holds true (the assumption made was effectively met).
- The cross-tabulation used is a 2x2 table, the degrees of freedom (df) for the test statistic is calculated as 1.
- The analogous p-value of the test statistic is very insignificant.
- "p = 0.000" or "p <.00001", the more accurate or mathematically precise statement would be "p < 0.001".

The Test Outcome and Conclusion

As the observed p-value is less as compared to opted level of significance that is $\alpha = 0.05$, the null hypothesis (Ho) could be rejected, and it could be reasonable to deduct that there exist some form of a relationship or linkage between the usage of AI in financial operations and efficiency so attained and this relationship on further analysis may result into higher efficiency attained with much higher and much better integration of AI in all financial operations and decision making at Financial Institutions.

Based on the calculations and the achieved values (results), the following could be safely state:

• There exists notable relationship or association as observed in between AI integration and operational and decision making efficiency so attained by various financial institutions as our Chi-Square value is 148.567 and, observed p < .001.

Checking the Correlation

To strengthen the analysis as well to interpret the relationship in a better manner Pearson Correlation was conducted. The closer analysis (table -4) indicates that there is correlation value (**r**) of .016 between values derived from implementing AI in organization (AI Functions) at the significance value (**p-value**) of .819. Further data suggests that higher the integration of AI in financial decision making better was considered the quality of decision making by the respondents. Respondents also agreed that decisions become more reliable and there is more comfort in going ahead with the decisions once they are backed up by the use of Artificial Intelligence.

Though the results attained for weak correlation (r) = .016 at p-value of .819 supports our null hypothesis as much of the relationship does not seems to exists between financial decision making and Artificial Intelligence. Key reason behind this finding might be less acceptability of AI in Financial Decision Making plus lower level of AI implementation in Indian Financial Sectors especially in Banks.

| - | · · · | Values | AI Functions |
|--------------|-------------------------|--------|--------------|
| | Pearson Correlation (r) | 1 | .016 |
| Values | Sig. (2-tailed) | | .819 |
| | N | 215 | 215 |
| AI Functions | Pearson Correlation | .016 | 1 |
| | Sig. (2-tailed) | .819 | |
| | Ν | 215 | 215 |

 TABLE 4 – Correlations (Values Derived and AI Functionality)

Further analysis for usage of AI within different sectors of financial industry (i.e. NBFC, insurance sector, Banking, Foreign Exchange dealers and Stock broking firms) and at different designations or hierarchical levels within each industry is cross checked so as to verify if AI holds more importance in one industry or may be at certain hierarchical level within the organization. May be the complexity and availability of time limit to take and execute a financial decision might be added more value by the usage of AI. Certain business functions and managerial levels might get more benefitted by the implementation of AI and certain might not find AI to be of any value at all.

An important observation to be considered while analysing the data is the key note relationship that exists between Correlation and 2-Tailed Significance level. The value observed for Pearson correlation and 2-Tailed Significance are complementary to each other, therefore both have to be deliberated vital while analysing the outcomes) where observed value of 2-Tailed Significance is less than 0.05, (significant at 95% confidence interval. The value of Pearson Correlation (r) and Significance (2-Tailed) value (p) would complement, i.e. if one value is found to be "acceptable" at that point the other value has to be considered "acceptable" too.

The Correlation output table below (table -5) showcases Pearson Correlations (r) between the pair i.e. Industry and AI Functionality. The results indicate that Industry influences the AI Functionality of the employees within the industry (r=.487, p=0.000). Observed levels of correlations (.487) below highlights the linearity of the relationship that exists between Industry and AI Functionality. Another important observation is that Correlation is considered significant at the 0.01 level (2-tailed). (This means the value will be considered significant if is between 0.001 to 0,010,.

The Value of Pearson Correlation (r) = .487 at (p) = 0.000 could be considered significant though the area under influence might not be very strong but their exist linear relationship that is semi-strong and influential as observed by the responses offered by the participants of the survey. In other words at all levels throughout different sectors of the financial industry AI functionality is considered important and the scope of AI functionality within financial decision making is considered as semi-strong or much needed though very strong form of the relationship has failed to emerge by the available data. One reason for the failure to get strong linear relationship could be once again the limited accessibility and usability of AI functionalities with in Financial Industry and hesitancy amongst the top echelon of management of the several institutions operational in India to make heavy investment in AI technology. There is still heavy reliance on human interface as observed within Indian Financial Industry and it might take Indian financial industry another decade to accept AI with open arms.

| | | Industry | AI Function |
|-------------|---------------------|-------------|-------------|
| Industry | Pearson Correlation | 1 | .487** |
| | Sig. (2-tailed) | | .000 |
| | Ν | 215 | 215 |
| AI Function | Pearson Correlation | $.487^{**}$ | 1 |
| | Sig. (2-tailed) | .000 | |
| | Ν | 215 | 215 |

 TABLE 5 – Correlations (Industry and AI Functionality)

**. Correlation is significant at the 0.01 level (2-tailed).

Reliability Testing

Reliability denotes consistency or uniformity, meaning that if you undertake certain standardized operation N times you are expected or should get approximately or roughly (rounded off) the same results or almost the same result all the times. In other words, Reliability is the extent of constancy, steadiness or uniformity, consistency of the test outcomes. Reliability could also be considered as the ability of a test (any test) or the research findings to be repeatable and expected to give same outcomes every time conducted on same data set.

Reliability coefficient is the degree or measure of how well a test (any selected test) processes or accurately calculates the achievement. It is the percentage or observed ratio of variance in final outcomes or calculated scores (i.e. scores achieved by applying the test), featured due to the theoretical "actual or genuine" score that would be obtained, if a perfect test existed else the variance would exist.

The need to calculate reliability emerged due to somewhat semi-strong linkage (r = 0.487) between AI functionality and Adoption and applicability in Industries and weak correlation (r = 0.16) that exists between Values derived and AI functionality, causing concerns and raising doubts about effectiveness of the instrument and the internal consistency that exists between all items within the questionnaire.

It would also be a predicament of research effectiveness and would help to identify any execution errors, if any were made during data collection or analysis stage.

As discussed above to measure reliability of internal items and consistency therein highlighting the effectiveness or the research instrument we have to use Reliability Coefficient. The "reliability coefficient" in reality denotes several different coefficients that could be used depending upon the design needs and requirements of the research as desired by the researcher. As discussed there exists several methods for calculating the coefficient including test-retest, parallel forms and alternate-forms and Cronbach's alpha is one of them and rather one of most commonly used measure that also acts as extensively used internalconsistency coefficient, this feature made it preferred tool to be applied for testing instrument reliability for this research.

| | | Ν | % |
|-------|-----------------------|-----|-------|
| | Valid | 215 | 88.84 |
| Cases | Excluded ^a | 27 | 11.16 |
| | Total | 242 | 100.0 |

TABLE 6 - Case Processing Summary

a. List wise deletion based on all variables in the procedure.

Table 6 above presents case processing summary indicating effectiveness of the responses being given by various participants to the research. It also highlights the valid respondents 88.84% of total (those who answered all 20 questions and responses were accurately measureable) and excluded 11.16% who failed to provide responses as desired by the research and needed to carry out research with reliability.

 TABLE 7 - Reliability Statistics - Cronbach's Alpha

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|------------------|--|------------|
| .876 | .877 | 20 |

Table 7 presents Reliability Statistics (standard and measurement of reliability of the instrument) as calculated inform of Cronbach's Alpha value of .876. The alpha coefficient as calculated for all the Twenty (20) items is observed as 0.876 or .876, suggesting that the items have very high level of internal consistency as observed by the test. We need to note that a reliability coefficient of value of .70 or higher, if observed or attained as test result is considered "acceptable" in maximum of research situations. The Score for this research is of .876 (Cronbach's Alpha) shows that the questionnaire is reliable and has very high level of internal consistency within all items included. Hence any doubt about research instrument reliability could be put to rest up to an extent and an effort could be initiated to look out for other observed relationships that could bring out much better understanding about efficacy of usage of AI within financial institutions or organizations in their decision making.

Calculating Analysis of Variance (ANNOVA)

Decision to calculate ANNOVA (Two Way) has been reached since the above two tests Chi-Square and Correlation did rejected the null hypothesis (Chi-Square) but failed to highlight the strength of relationship (Correlation) that may exist between AI Functionality and Financial Decision Making in Financial Institutions and AI Functionality and its Value (importance and usability) for different Organizations.

ANNOVA (Two Way) was considered more suitable as the data had dependent variable that could be measured in intervals and in absolute numbers (performance and ease of decision making), two independent variables has several categories (positions of respondents and organizations belonging to different financial sectors), different and non-repetitive participants (independence of observation), lesser number of outliers or extremities in observation (data had not more than 5% outliers)

| [| | | Sum of | df | Mean | Friedman's | Sig |
|------------------|---------------|---------------|---------------------|-------|--------|------------|------|
| | | | Squares | | Square | Chi-Square | |
| Between People | | 550.062 | 212 | 2.595 | | | |
| Within People | Between Items | | 1571.375 | 19 | 82.704 | 51.077 | .000 |
| | | Nonadditivity | 52.486 ^a | 1 | 52.486 | 32.669 | .000 |
| | Residual | Balance | 6469.640 | 4027 | 1.607 | | |
| | | Total | 6522.125 | 4028 | 1.619 | | |
| | Total | Total | | 4047 | 2.000 | | |
| Total | | 8643.562 | 4259 | 2.029 | | | |

TABLE 8 - ANOVA with Friedman's Test and Tukey's Test for Nonadditivity

Grand Mean = 3.06

a. Tukey's estimate of power to which observations must be raised to achieve additivity = .555.

Table 8 above has Friedman's Chi-Square test statistic as 51.077 and significant at .000 the data so obtained in table 8 further justifies the inclusion of all most all of the variables i.e. indicating that the variables selected are correct and apt for the model, to be used in testing the effectiveness of correlation between AI and Financial Decision Making within Indian Financial Organizations that too across various job positions and activity centres and sectors within the financial industry. It helps in proving the efficacy of AI usage to an extent.

Another important benchmark measure is the standardized residual value as displayed in the table 8 above is a significant positive value of 52.486, significant at .000 indicating that Artificial Intelligence is rightfully represented in the actual sample when compared to the expected frequency and AI is acceptable to a great extent by the sample respondents. Participants' responses towards AI integration in Financial Decision making are positive in

all parameters and ANOVA results thus obtained reveal that there is no significant difference between the participants' perspectives on adoption of AI and its integration with financial decision making across financial organizations and official job positions.

This showed that there were more intricacies involved within the variables than actually were expected. Results thus obtained reveal an important fact that on an average, there is a significant increase in Financial Decision Making that is done through the usage of Artificial Intelligence. Acceptance of AI within financial organization is on rise and respondents are ready to accept AI as they know it will bring more effectiveness in their working and would make their work-life easy.

To conclude

AI and its usage in Indian Financial Industry presents mixed picture as top managements are bit skeptical to make investments in AI due to margin and operational pressure. The sorry state of the Indian Economy and pressure on the Financial Sector to lend to government plus to tidy up their books and generate cheap funds along with supporting Indian Stock Market has made the environment quite volatile. Though the employees at all levels feel that usage of AI and its complete integration with in systems would be a great advantage for them and would make their life simple. Though the respondents also sounded the word of caution that in the industry so susceptible to risk and facing so many challenges could not rely on technology and AI and need to use Human Intelligence and reliance of Human intellect is and would be of utmost importance even after complete integration of AI takes place and AI is not a perfect alternative to Human Intelligence.

As the old saying goes two heads are better than one — especially if the second one is an AI that could provide you with ready solutions to difficult problems and issues making your work life simplified. AI and Machine Learning supporting decision making are just gaining popularity as Decision Solution Systems, early researches have shown that these systems have very robust viability and proven capabilities in generating incremental Return On Investment. These Decision analytics tools and Solution Systems could facilitate the process moreover could power up decision-making, provide the right insights at the right time.

Several financial institutions in India are lagging behind in adoption of AI or even Machine Learning at all levels, some of the senior positions working in banking or financial services are finding it problematic to persuade the team members (especially the subordinates) or for some even top executives are difficult to make understand, to accept an AI solution to effectively encounter present-day operational challenges faced by the organizations. It is essential to highlight that AI has already begun to form waves of disruption through the Indian Financial Sector, currently not all players might be having the much needed understanding and awareness that is vital to contemplate how AI could become a great support to effectively meet out challenges of the future plus the adoption process is quite slow and progress of Indian financial industry when compared with global benchmarks (International Financial Industry's Adoption of AI) could be termed as laggard.

References

- [1] Abdou HA, Alam ST, Mulkeen J. Would credit scoring work for islamic finance? A neural network approach. International Journal of Islamic and Middle Eastern Finance and Management. 2014;7(1).
- [2] Altman EI. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. J Finance. 1968;23(4):589-609.
- [3] Altman EI, Marco G, Varetto F. Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience). J Bank Financ. 1994;18(3):505-529.
- [4] Alzaidi A. Impact of Artificial Intelligence on Performance of Banking Industry in Middle East. IJCSNS International Journal of Computer Science and Network Security. 2018;18(10):140–148.
- [5] Bagheri A, Mohammadi Peyhani H, Akbari M. Financial forecasting using ANFIS networks with Quantum-behaved Particle Swarm Optimization. Expert Syst Appl. 2014;41(14):6235-6250.
- [6] Bahrammirzaee A. A comparative survey of artificial intelligence applications in finance: artificial neural networks, expert system and hybrid intelligent systems. Neural Comput Appl. 2010;19(8):1165-1195.
- [7] Chan, C., Chow, C., Wong, J., Dimakis, N., Nayler, D., Bermudes, J., Raman, J., Lam, R., & Baker, M. Artificial Intelligence Application in Financial Services.; 2019.
- [8] Chavarnakul T, Enke D. Intelligent technical analysis based equivolume charting for stock trading using neural networks. Expert Syst Appl. 2008;34(2):1004-1017.
- [9] Dempster MH, Payne TW, Romahi Y, Thompson GP. Computational learning techniques for intraday FX trading using popular technical indicators. IEEE Trans Neural Netw. 2001;12(4):744-754.
- [10] Duygun-fethi M, Down C, Jackson G. Assessing bank performance with operational research and artificial intelligence techniques: A survey. Published online 2009. Accessed May 24, 2021. http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.473.4002
- [11] Eletter, S. F., Yaseen, S. G. & Elrefae, G. A. (2010). Neuro-Based Artificial Intelligence Model for Loan Decisions. American Journal of Economics and Business Administration, 2(1), 27-34. https://doi.org/10.3844/ajebasp.2010.27.34

- [12] Fethi MD, Pasiouras F. Assessing bank performance with operational research and artificial intelligence techniques: A survey. SSRN Electron J. Published online 2009. doi:10.2139/ssrn.1350544
- [13] Fethi, Meryem Duygun and Pasiouras, Fotios, Assessing Bank Efficiency and Performance with Operational Research and Artificial Intelligence Techniques: A Survey (February 27, 2009). European Journal of Operational Research, 2010, 204 (2), 189-198 (Revised Version)
- [14] Giudici P. Fintech risk management: A research challenge for artificial intelligence in finance. Front Artif Intell. 2018;1:1.
- [15] Hawley DD, Johnson JD, Raina D. Artificial neural systems: A new tool for financial decision-making. Fin Anal J. 1990;46(6):63-72.
- [16] Hussain AJ, Al-Jumeily D, Al-Askar H, Radi N. Regularized dynamic self-organized neural network inspired by the immune algorithm for financial time series prediction. Neurocomputing. 2016;188:23-30.
- [17] Khandani AE, Kim AJ, Lo AW. Consumer credit-risk models via machine-learning algorithms. J Bank Financ. 2010;34(11):2767-2787.
- [18] Kumar N, Srivastava J, Bisht H. Artificial Intelligence in Insurance Sector. Journal of the Gujarat Research Society. 2019;21(7):79–91.
- [19] Kumar S, Aishwaryalakshmi S, Akalya A. Impact and Challenges of Artificial Intelligence in Banking. Journal of Information and Computational Science. 2020;10(2):1101–1109.
- [20] Lee M-C, To C. Comparison of support vector machine and back propagation neural network in evaluating the enterprise financial distress. Int J Artif Intell Appl. 2010;1(3):31-43.
- [21] Patel K. Artificial Intelligence in Finance. International Journal for Scientific Research & Development. 2018;4(4):2787–2788.
- [22] Patil K, Kulkarni M. Artificial Intelligence in Financial Services: Customer Chatbot Advisor Adoption. International Journal of Innovative Technology and Exploring Engineering (IJITEE. 2019;9(1):4296–4303.
- [23] Tilakaratne CD, Mammadov MA, Morris SA. Effectiveness of using quantified intermarket influence for predicting trading signals of stock markets. In: Australian Computer Society; 2007:171–179.
- [24] Van Liebergen B. Machine learning: A revolution in risk management and compliance? Journal of Financial Transformation. 2017;45:60–67.
- [25] Varetto F. Genetic algorithms applications in the analysis of insolvency risk. J Bank Financ. 1998;22(10-11):1421-1439..
- [26] Vijay C. Artificial intelligence in Indian banking sector: challenges and opportunities. International Journal of Advanced Research. 2019;7(5):1581–1587.
- [27] Xing FZ, Cambria E, Welsch RE. Natural language based financial forecasting: a survey. Artif Intell Rev. 2018;50(1):49-73.
- [28] Zavadskaya A. Artificial Intelligence in Finance: Forecasting Stock Market Returns using Artificial Neural Networks. Published online September 29, 2017. https://helda.helsinki.fi/dhanken/bitstream/handle/123456789/170154/zavadskaya.pdf?s equence=1

Online Resources

- [1] Pwc.com. Accessed March 18, 2021. https://www.pwc.com/gx/en/news-room/docs/report-pwc-ai-analysis-sizing-the-prize.pdf
- [2] The state of AI in 2020. Mckinsey.com. Accessed April 2, 2021. https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/globalsurvey-the-state-of-ai-in-2020
- [3] Oliverwyman.com. Accessed on April 5, 2021. Marsh and McLennan Companies. https://www.oliverwyman.com/content/dam/oliverwyman/v2/publications/2019/dec/ai-app-in-fs.pdf
- [4] internationalbanker. Autonomous finance is the future. Internationalbanker.com. Published April 16, 2021. Accessed April 21, 2021. https://internationalbanker.com/finance/autonomous-finance-is-the-future/