A proposed method with a use case to facilitate the decision of implementing new technology in insurance organizations to improve operational efficiency

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Abstract: Enhancing operational efficiency is a key for any business. Insurance business is one such industry where this plays a significant role. Enhancing operational efficiency in insurance is not straightforward owing to the complex underlying business structure and stringent regulation that prevails. One of the ways of enhancing the operational efficiency in an insurance organization is by implementing new technology in the business and seamlessly integrating with the underlying insurance operations involved. Integration of new technology will enhance the other two components of operational efficiency – process and people. Enhancing the speed of the process, reducing errors and solving macro level are achieved with new technology which could not be addressed earlier due to the magnitude and the challenges involved in solving the same. But for implementing new technology in insurance operations, it is very much essential to assess the various challenges and opportunities involved in implementing the same. We propose a methodology to assess the impact of new technology adaptation by analyzing how different levels and operations of an insurance organization is impacted by the implementation of the new technology. This is a scoring mechanism which will give a consolidated score across various operations and levels. Based on the organization's business structure, risk appetite along with this score, it can decide whether to implement the new technology or not. This work also gives a use case built on the assessment of the implementation of AI and deeplearning models in insurance operations based on the proposed methodology.

***IndexTerms* - Actuarial control cycle, Claims handling, Underwriting, Fraud detection, Pricing, InsurTech**

I. INTRODUCTION

The advancement and the growing trends in Science and Technology has affected several industries with time across the globe. One such industry which got significantly affected by this is the financial services. In the financial services, different sub-sectors have adopted the new technology at different rates over time. The insurance industry is one sub-sector where this adaptation is slower than the others like that of the banking services. History shows that the insurance industry is a slow adapter to the new technology. One of the reasons for this is the high running costs of incumbent systems. This leads to lower budgets available for innovation compared to the banking sector. There are several other reasons for the slow rate in technological adaptation. They are strict regulations, complex structure of the underlying business and most importantly the ubiquitous presence of the insurance industry across all the other industries and the lives of people.

At the start of the 21st century, the insurance industry had limited considerations and issues like the conflict between the actuarial and the marketing departments on product pricing. The rise of technology in insurance namely the InsurTech, has opened the industry into a great deal of opportunities which are both exciting and scary. Thus, it has lead the industry into a lot more considerations other than just product pricing.

Technology adaptation in insurance is what all the companies and institutions talk about. Yes, technology is the way into the future. It has taken this significant spot for its immense utility and capabilities of doing things which would either not be possible or feasible to achieve by the people. It can speed up several processes, analyze a huge amount of data and make interpretations and significantly cut down the cost of human capital in any organization. But, new technology adaptation in an insurance organization is not a readily implementable process. Before implementing a new technology in an existing operation in an organization, it should clearly identify the various risks involved in implementing the same. Some of them can be, high costs of implementing the new technology, significant amount of training to be given to various stakeholders in adapting to the new technology, the regulations that come along with the new technology, high costs new systems and other resources needed to aid the implementation, the steepness of the learning curve for the adaptations to name a few. Thus, it is necessary for an organization to clearly evaluate the risks and benefits involved for the adaptation of the new technology. This new technology adoption also includes off-the shelf Insure tech products into the organization which are implemented in various functions. For eg. Policy Admin System. Agents Compensation System, Billing System, Accounting System etc. Each of these packages are evaluated based on the functionality requirements of the organization along with the technological advantages that it brings along.

This work is divided into 5 sections. Section 1 introduces the topic of the entire work. Section 2 tells the motivation behind this work. Section 3 talks about the proposed method which is used for the implementation of new technology in an insurance organization evaluating with a help of a toolbox. Section 4 presents a use case of the above tool box on the implementation of AI and deep learning methodologies in insurance organizations. Section 5 presents the conclusions drawn in this work and the analysis of the use case.

II. MOTIVATION

The biggest advantage of implementing new technology in insurance business is the enhancement of operational efficiency in an organization. Companies strive to be more efficient in their operations by analyzing different operations and see how technology can be involved to make them more efficient. With the help of technology, many complex problems could be solved and many new problems can be addressed. Thus, technology rise has immense applications and utility into the operations of an insurance company. But, there are various concerns and problems in blindly implementing the same within the company. These impact significantly the core business operations, also bring along new concerns and risks which weren't there earlier. Thus an insurance company before implementing or adopting new technology should see the impact in its operations, the costs of implementing the same, the impact on the external environment, the concern of various stakeholders, the cost benefit analysis to name a few. This paper is aimed on facilitating the decision making on the implementation of new technology in an insurance organization. We propose a methodology to aid the insurance organizations better in addressing various subtle aspects involved and the nuances at various levels and functions in the organization in implementing new technology.

III. The Proposed Method

The following is the checkpoint toolbox which is built for different levels and aspects for an insurance company. This toolbox is divided into several subsections based on the level and the aspect of operations in an insurance organization. For different levels and aspects, this toolbox contains a list of checkpoints to be considered while implementing and adopting a new technology. The response for each of the points is categorized into 3, namely the Categorical – Yes/No, Ratios and percentages and other numerical values. The values for each of the response would be dependent on the operations of the company, the process which is going to be automated and the new technology which is going to be implemented. The categorical variables take the numbers +1 or -1 depending on the response and corresponding checkpoint. At the end of every subsection in the toolbox, a key is present which would assign numerical values according to the corresponding checkpoint.

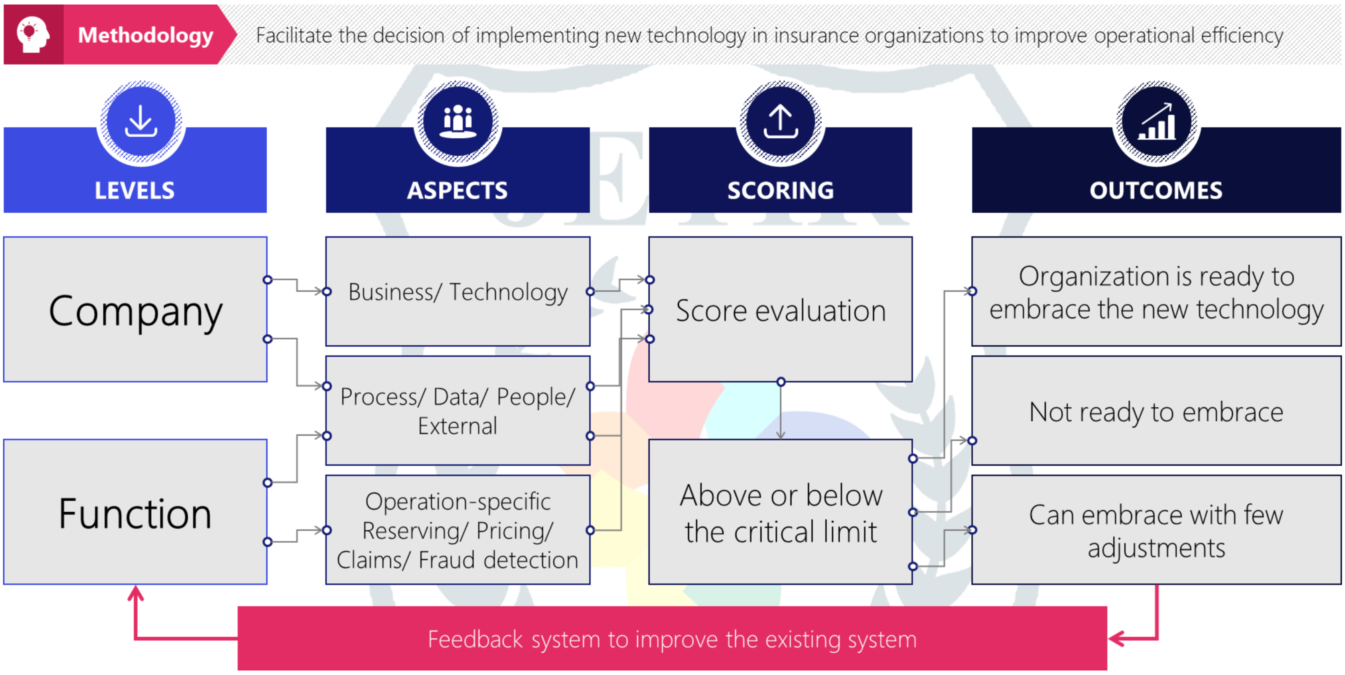

Figure 1 - Methodology

Table 1 - Checkpoints – Level: Company, Aspect: Business

S.no	Level	Aspect	Checkpoint	Measure	Variable name
1	Company	Business	Does it affect customer experience positively?	Y/N	CAT 1
			If 1 yes, go to a.		
			a) Does it complicate the experience for a customer	Y/N	CAT 2
2	Company	Business	Does regulations have an effect directly?	Y/N	CAT 3
3	Company	Business	Does legislations have an effect directly?	Y/N	CAT 4
4	Company	Business	Is there an outsourcing opportunity available?	Y/N	CAT 5
			If 4 yes, go to a.		
			a) Can outsourcing reduce the cost?	Y/N	CAT 6
			b) Is the time taken reduced by outsourcing?	Y/N	CAT 7
			c) Would a takeover or a merger simplify the process?	Y/N	CAT 8
			d) Would a takeover or a merger reduce the costs?	Y/N	CAT 9
5	Company	Business	Will the core business structure get affected?	Y/N	CAT 10
			If 5 yes, go to a.		
			a) Would the structural change would receive foreseeable benefits?	Y/N	CAT 11
			b) Would majority of the stakeholders agree for the change?	Y/N	CAT 12
			c) Is there a provision in place for handling this impact at a functional level?	Y/N	CAT 13
6	Company	Business	Is the industry trying to embrace this technology?	Y/N	CAT 14
7	Company	Business	Have the competitors started to embrace this technology?	Y/N	CAT 15

8	Company	Business	Have the companies in other industry adopted a similar technology change?	Y/N	CAT 16
9	Company	Business	Is there a comprehensive program to implement the new technology?	Y/N	CAT 17
10	Company	Business	Is there a comprehensive program to train the people for the new technology?	Y/N	CAT 18
11	Company	Business	Is there a contingency plan for employee turnover?	Y/N	CAT 19
12	Company	Business	Is there a monitoring mechanism in place?	Y/N	CAT 20
13	Company	Business	Are there metrics present to measure the success of the implementation?	Y/N	CAT 21

Response Key for Table 1

For CAT 2,3,4,6,7,8,9 Value of yes is -1, Value of no is +1
For CAT 11 to 21 Value of yes is +1, Value of no is -1

Table 2 - Checkpoints – Level: Company, Aspect: Technology

S.no	Level	Aspect	Checkpoint	Measure	Variable name
14	Company	Technology	Is there an avenue available for a technological upgrade?	Y/N	CAT 22
15	Company	Technology	Is there a significant familiarity with the new technology?	Y/N	CAT 23
16	Company	Technology	Are there sufficient resources and facilities available for the technology adoption?	Y/N	CAT 24
17	Company	Technology	Is there a significant amount of new expertise required ?	Y/N	CAT 25
18	Company	Technology	Is the in house technological expertise sufficient for the change?	Y/N	CAT 26
19	Company	Technology	Are the best practices available and considered for the new technology?	Y/N	CAT 27
20	Company	Technology	Would a significant amount of systems and other resources rendered obsolete because of the new technology?	Y/N	CAT 28
21	Company	Technology	Is there an active risk for a cyber-security breach?	Y/N	CAT 29
22	Company	Technology	Is there a contingency plan present for a cyber-security breach?	Y/N	CAT 30

Response Key for Table 2

For CAT 22-24, 26,27,30 Value for yes is -1, Value for no is +1
For CAT 25,28,29 Value for yes is +1, Value for no is -1

Table 3 - Checkpoints – Level: Function, Aspect: Process

S.no	Level	Aspect	Checkpoint	Measure	Variable name
23	Function	Process	Are the processes within a department is categorized from simple to complex?	Y/N	CAT 31
			If 23 yes, got to a		
			a) What is the percentage of the process considered simple?	Percentage	RAT 1
			b) Is the new technology for any simple process?	Y/N	CAT 32
24	Function	Process	The number of processes within the function directly linked to the process going to be upgraded with the technology?	Number	NUM 1
25	Function	Process	Is there a technological audit done for the existing process compared to the new one?	Y/N	CAT 33
26	Function	Process	What percent of the process has human intervention?	Percentage	RAT 2
27	Function	Process	What is the percent of the people in the particular function involved in the same?	Percentage	RAT 3
28	Function	Process	Is the process repetitive in nature?	Y/N	CAT 34
29	Function	Process	What percentage of work is repetitive for an individual within the process?	Percentage	RAT 4
30	Function	Process	How many times is that process repeated in a given time?	Number	NUM 2
31	Function	Process	Is there an explicit regulatory intervention present?	Y/N	CAT 36

Response Key for Table 3

For CAT 31,32,33,34 Value for yes is +1, Value for no is -1
For CAT 36 Value for yes is -1, Value for no is +1

Table 4 - Checkpoints – Level: Function, Aspect: Data

S.no	Level	Aspect	Checkpoint	Measure	Variable name
32	Function	Data	How many sources of data is required for the process?	Number	NUM 3
33	Function	Data	What is the amount of data involved?	Number	NUM 4
34	Function	Data	Is the data classified according to its nature and type?	Y/N	CAT 37
			If 34 yes, go to a		

			a) How much is categorical?	Number	NUM 5
			b) What is the nominal to ordinal ratio?	Number	NUM 6
			c) Is the data imbalanced?	Number	NUM 7
			d) What is the percentage of null values in the data?	Number	NUM 8
35	Function	Data	What is the amount of time required in data pre-processing?	Number	NUM 9
36	Function	Data	What is the percentage of relevant data that is put into use?	Percentage	RAT 5
37	Function	Data	What is the percentage of data which is interpreted manually?	Percentage	RAT 6
38	Function	Data	What is the ratio of structured data to unstructured?	Percentage	RAT 7
39	Function	Data	How types of unstructured data are present?	Number	NUM 10
40	Function	Data	What is the time taken for cleaning done for the unstructured data?	Number	NUM 11
41	Function	Data	Is it converted into a structured format?	Y/N	CAT 38

Response Key for Table 4

For CAT 37,38 Value for yes is +1, Value for no is -1

Table 5 - Checkpoints – Level: Function, Aspect: People

S.no	Level	Aspect	Checkpoint	Measure	Variable name
42	Function	People	What is the number of people involved in the process?	Number	NUM 12
43	Function	People	What is the percentage of human interaction involved in the process?	Percentage	RAT 8
44	Function	People	What is the amount of work which is time consuming?	Number	NUM 13
45	Function	People	What is the percentage of work which is repetitive?	Percentage	RAT 9
46	Function	People	Is the required technological expertise present?	Y/N	CAT 39
			If 46 yes, go to a		
			a) What is the percentage of people having the required technological expertise?	Percentage	RAT 10
47	Function	People	What percent of the time is spent on more complex process after handling the simple ones?	Percentage	RAT 11

Response Key for Table 5

For CAT 39 Value of Yes is +1, Value of No is -1

Table 6 - Checkpoints – Level: Function, Aspect: External

S.no	Level	Aspect	Checkpoint	Measure	Variable name
48	Function	External	Is the process affected significantly by regulation?	Y/N	CAT 40
49	Function	External	Is the process affected significantly by Accounting Standards?	Y/N	CAT 41
50	Function	External	Is the process affected significantly by Tax?	Y/N	CAT 42
51	Function	External	Is the process affected significantly by Interest Rates?	Y/N	CAT 43
52	Function	External	Is the process affected significantly by Inflation?	Y/N	CAT 44
53	Function	External	Is the process affected significantly by Exchange Rates?	Y/N	CAT 45
54	Function	External	Is the process affected significantly by Risk Management Functions?	Y/N	CAT 46
55	Function	External	Is the process affected significantly by Solvency?	Y/N	CAT 47
56	Function	External	Is the process affected significantly by Capital Adequacy?	Y/N	CAT 48
57	Function	External	Is the process affected significantly by Demographic trends?	Y/N	CAT 49
58	Function	External	Is the process affected significantly by Life style considerations?	Y/N	CAT 50
59	Function	External	Is the process affected significantly by Institutional Structure?	Y/N	CAT 51
60	Function	External	Is the process affected significantly by Social Trends?	Y/N	CAT 52
61	Function	External	Is the process affected significantly by State Benefits?	Y/N	CAT 53

Response Key for Table 6

For CAT 40 to 53 Value of Yes is -1, Value of No is +1

Table 7 - Checkpoints – Level: Function, Aspect: Specific – Claims

S.no	Level	Aspect	Checkpoint	Measure	Variable name
62	Function	Specific-Claims	How many claims are handled in a given period?	Number	NUM 14
63	Function	Specific-Claims	How many different types of claims are handled?	Number	NUM 15
64	Function	Specific-Claims	What is the average time taken to settle a claim?	Number	NUM 16
65	Function	Specific-Claims	What is the percentage of claims coming post a court ruling?	Percentage	RAT 12

66	Function	Specific-Claims	How much percentage of data can be significantly obtained from the claimant notes?	Percentage	RAT 13
67	Function	Specific-Claims	What is the average customer satisfaction during the claim settlement process?	Number	NUM 17
68	Function	Specific-Claims	What is the average customer satisfaction while interacting with the claims handler?	Number	NUM 18

Table 8 - Checkpoints – Level: Function, Aspect: Specific – Fraud

S.no	Level	Aspect	Checkpoint	Measure	Variable name
69	Function	Specific-Fraud	Are there fraud detection system already available in place?	Y/N	CAT 54
			If yes, then go to a		
			a) Is it a rule-based fraud detection system	Y/N	CAT 55
			b) Is it a ML-based fraud detection system	Y/N	CAT 56
70	Function	Specific-Fraud	What is the percentage of fraud found by the existing system?	Percentage	RAT 14
			If percentage is available, then go to a		
			a) Is it below the average fraud rate in the industry?	Y/N	CAT 57
			b) Is there a need to improve the existing system by incorporation AI?	Y/N	CAT 58
71	Function	Specific-Fraud	Is the industry trying to use AI into fraud detection system?	Y/N	CAT 59
72	Function	Specific-Fraud	Have the competitors started to embrace this technology?	Y/N	CAT 60
73	Function	Specific-Fraud	Are there any regulatory pressure to improve the existing system	Y/N	CAT 61
74	Function	Specific-Fraud	Are there metrics present to measure the performance of the model?	Y/N	CAT 62
75	Function	Specific-Fraud	Is the in-house technological expertise sufficient for the change?	Y/N	CAT 63
			If no, then go to a		
			a) Are there sufficient resources and facilities available for the technology adoption?	Y/N	CAT 64
			b) Is there a significant amount of new expertise required?	Y/N	CAT 65
76	Function	Specific-Fraud	What percent of the process has human intervention?	Percentage	RAT 15
77	Function	Specific-Fraud	Are there any available past data/experience for the model training?	Y/N	CAT 66
78	Function	Specific-Fraud	Is the data classified according to its nature and type?	Y/N	CAT 67
			If yes, then go to a		
			a) How much is categorical?	Percentage	RAT 16
			b) Is the data labelled?	Y/N	CAT 68
			c) Is the data imbalanced?	Y/N	CAT 69
			d) What is the percentage of the dataset is missing?	Percentage	RAT 17
79	Function	Specific-Fraud	What is the target fraud detection rate expected by new technology?	Percentage	RAT 18

Response Key for Table 8

For CAT 55, 57-64, 66-69	Value of Yes is +1, Value of No is -1
For CAT 54, 56, 65	Value of Yes is -1, Value of No is +1

Tables 1 and 2 are industry level assessments on business and technology. Tables 3,4,5 and 6 are common for every function in the insurance company. Thus for any level of new technology implementation, these are the 6 basic tables which has to be responded. Tables 7 and 8 are specific to certain insurance operations. Table 7 is a list of checkpoints specific to particular claims function. Table 8 is a list of checkpoints specific to a particular insurance fraud functionality. These 2 are specific tables that are only responded when the new technology has a direct impact on the given operations. Similar tables can be built specific for individual operations like pricing and reserving to name a few.

Decision making

Once the responses for all the checkpoints are obtained, a weighted average should be calculated for the same. As mentioned earlier, the values obtained are dependent on the operations of the company, the process which is going to be automated and the new technology which is going to be implemented. The corresponding weights for calculating the weighted average is determined by the company's core business structure, risk appetite, technological expertise and competition to name a few. Once these weights are obtained from the company, the weighted average can be calculated. The critical point for this average is also decided by the management. Thus, the final decision to on whether to implement the new technology or not would depend whether the weighted average is above the critical point or not.

IV. Use Case - Assessment of the implementation and adoption of AI into the insurance operations

Thus, the above method is used as a toolbox for the assessment on whether to implement and adopt AI and deeplearning algorithms in its operations for several functions or not. The following are the set of assessments obtained from the toolbox on several benefits and the shortcomings of implementing the same for various functions. It also has the inferences of the assessment obtained and brief notes explaining the reasons behind those benefits and shortcomings which were indicated by the model.

a) Assessment on customer experience

The modern times offers a policyholder with wide variety of insurers and the products to choose from than any time before. Thus, more and more potential and the current policyholders review their insurance requirements and try switching between the insurance companies. The market clearly tells us that the best product is no longer the cheapest product. The real differentiator is the offerings based on the technology which lure the customers move towards a particular product. This maybe the use of technology for better underwriting in order to understand the customer needs better, or in claims handling where the use of technology makes the claims processing free from bias due to lesser human interaction, more precise and processed faster. Thus, there is an increase in net promoter score and customer satisfaction.

For both financial institutions and technological firms, enhancing the experience of customers is a key factor. For any technological transformation focused on insurance, the journey of the customer is the heart of any development. Consumers in the modern times do not want to wait for the monthly report or wait in long lines. They demand real-time engagement and access services online on the platforms like their phones and personal computers. This forces the insurance companies to move towards a paper free environment and into a world of digital ecosystem with as less manual interventions as possible.

But, there has been a significant increase in the complications on the process of obtaining an insurance policy over time for people. It has been observed in the health insurance sector that majority of the people do not make the best choice among the plans in front of them. George Loewenstein of Carnegie-Mellon University said that it was rather a dreading process for him to pick a plan for his son. There are a significant number of people who are new to the world of insurance. Thus while trying to get a best policy online generated by an algorithm without any human interaction will not give them enough confidence with the policies and tend to lapse them over time.

b) Assessment on Underwriting

There has been a lot of interest in this area in the recent times. Companies are trying to move in this area to automate underwriting using AI and rule based engines. This can effectively move the process of underwriting into a higher level of sophistication and increase the efficiency manifolds. Automatic underwriting has a lot of benefits. Some are, the time taken to underwrite is reduced drastically, in turn increasing the customer satisfaction. It is less biased since the final decision is purely data driven. Minimum human intervention, thus reducing the underwriting costs significantly for the company. Many companies try to partner with some software providers to come up with this tool.

Though having this tool has a lot of advantages, there are factors which the insurance companies should be concerned about.

- The software provider would take about 12 months to get the underwriting engine into the business infrastructure of the insurance company. This happens after the time when the company decides to have an underwriting engine. Thus, to implement this tool into the business will take a lot of time.
- The price to purchase or the costs to build an underwriting engine would just be the beginning of the company's expenditure on technology.
- This tool would increase the efficiency of the process, but it would reduce the effectiveness of the process. The reason is because, technology would process the poorly underwritten business the same way it does with the properly assessed cases.
- Though this engine is effective for data driven decision making for preferred risk assessment, a qualified underwriter is required to handle the assessment of the impairment risks.

Thus, the implementation of this engine does not reduce the headcount of the underwriters in the company. It acts as a tool to boost the efficiency by partially automating the workflow.

c) Assessment on Pricing and Product Design

AI can be used to study the correlations among the places, people and the policies taken. Thus, it can bring out significant correlations present in the data along with the demographics in order to predict the type of products and its pricing people in a particular place can possibly buy. It can also create new types of policies with the correlations in order to appease the potential customers. But there is a problem in this. The algorithm would most likely not consider the external environment like the legislation and regulation and the effect of each of the product on the companies' asset structure. Thus, the best product generated by the algorithm would not be the best product in the real world.

AI can be used for pricing different policies. By studying volumes of underwriting data, AI can be used to study the features and price the products based on the past experience. This can reduce the process of insurance underwriting drastically and the entire process can be automated and also built as a mobile application. Thus, people can fill the form online and they will get an instant quote generated by AI. Though this can be helpful for simple policies, there are several externalities like the law and regulations present for complex policies. This cannot be done efficiently by the AI and would require a pricing team in order to price a product and quote the same.

d) Assessment on Claims Handling

Claims handling is one of the process which involves human interaction. This is a time consuming process. The claim adjusters have to settle the claims of all the claimants by analyzing the damage carefully. This process of settling claims by the claims adjuster has several disadvantages.

- It is a time consuming process. The claimants have to wait for a long time for the claims to be processed.
- There would be a significant amount of bias in this process since it also in a way the mindset and the feelings of the claims handler.
- It is a difficult task of text processing to understand the claimant notes while handling each claim. These also can be hand written with the usage of acronyms making it difficult to decipher and make meaning out of this unstructured data.

Thus, having an automatic claims handler can be a huge advantage to the insurance company to overcome the above mentioned difficulties. The automatic claims handler would be built on the data using several machine learning and deep learning algorithms to understand the features and the patterns in the data. This tool will give faster and at times more accurate results which would be free of any bias.

Though this concept of an automatic claims handler looks promising, it has some disadvantages as well. There are certain cases where human intervention is inevitable. If the claim involves a bodily injury or a death of a person, a simple computer algorithm would not be used to handle that claim. So many external factors affect the final claim amount. Few of these factors are:

- The nature of the injury
- The court ruling
- The earning capacity of the person injured or died
- The local legislation

Thus, for bodily injuries and death related claims, there should be a claims handler present in order to process the claims. In these types of cases, the automatic claims handler can redirect the claims to the available claims handler to process the same.

e) Assessment on other Actuarial Tasks

There is a growing concern in the actuarial world over the dominance of AI for decision making. One big reason is that more and more real world problems can be tackled by the machine learning and deep learning algorithms. The technology can learn and improve better than humans can adapt to the new problems. Machine learning algorithms unlike actuaries can work on large chunks of data produced by the financial services institution and can give out accurate rates within minutes. Another advantage of the machine learning over men is that their performance remains constant with time and does not drop. In other words, they do not become old! They deliver the results without taking in the externalities of pressure to deliver. Thus, these algorithms reduce the costs to the company, reduces the human dependency, improves the reliability of work and reduces the risk of business disruptions that come along in the actuarial teams.

Having said that, there is another side to the story. Yes, machine learning has been doing significantly well in taking away certain functionalities away from a human actuary. But, the current development of these algorithms are in the stage where it still requires human intervention for a smooth flow of work. Especially in the world of financial analytics, the level of automation using machine learning is not yet there for ungoverned use. The human brain can process far more parallel sets of information and make highly complex judgements based on the past records than the machine learning algorithms as of this date and in near foreseeable future. Even the advanced algorithms of deep learning are still put into use only in clear cut and confined problems.

But because of the agility in the world of actuarial science, people have started to find synergy with the growing technological trend than seeing them as a threat to their existence. The Actuaries of the future are those actuaries apart from the expertise in handling risk have the technical skillsets to come up with advanced machine learning algorithms for problem solving. Thus, they find the right way for unlocking the potential of these algorithms. Actuaries no longer are expected to work on traditional ways of solving the problems of pricing and reserving. Coming up with new models and ways of extracting the potential from the data like analyzing the individual claims data and policy data in real time. These actuaries see a lot of potential of solving various problems outside the insurance business. Thus, the actuaries with technological background are much valuable in today's market than the traditional actuaries. Realizing the immense potential of these breeds of actuaries, several top actuarial bodies like Society of Actuaries(USA) and Casualty Actuarial Society(USA) have come-up with data science credentials for actuarial students and some bodies like IAI (India) and IFoA(UK) also orienting their curriculum and exams towards data science.

f) Assessment on Fraud Detection

Use of Artificial Intelligence (AI) in insurance fraud detection provides the ability to automatically improve and learn fraud patterns from the data provided without programming it explicitly. The process of "learning" starts from the observation of data in order to look for patterns in the data provided. Today there is a rapid growth of application of AI/machine learning in the insurance sector. It indicates how rapidly the industry is embracing AI, thereby implying its importance. The ability to use machine learning to process data would provide valuable analytical insights, this would help insurance companies gain a competitive advantage. ML-based fraud detection models allow the organization to process big data and find hidden relation between claim profile and a likely fraudulent behavior. However, the current world is still dominated by rule-based fraud detection systems in comparison to ML-based fraud detection models. The major drawback of these systems are that they are not flexible and requires too much of manual work to incorporate all the fraud detection rules. Use of AI in rule based engines with can help find complex rules and also be configured to allow for changing business environment.

There are various challenges that the insurers face in implementing machine learning for fraud detection. Some of the challenges being:

- Availability of correct data – one major challenge that is faced when using such models is the availability of data in the right format.
- Availability of fraudulent data – in order to train the model a significant amount of fraudulent data would be required. This is a challenge as the fraudulent data is highly unbalanced in nature.
- Data security – training AI models require a huge amount of data, this has created data security issues for the organization, as they are vulnerable to cyber-attacks and other related threats.

Though there are some challenges and difficulties associated with incorporating AI into the fraud detection model, there is no denying the fact that machine learning models are better than traditional predictive models for fraud detection.

g) Assessment on Solvency

This department is similar to that of capital adequacy, but has more vigilant monitoring by the regulator and the company. Technology and AI can be used to study the data of solvent and insolvent companies at an industry level to determine the metrics indicating a potential failure. The disadvantage of this is that, there aren't many cases of failed insurance companies in India. Thus, the companies study would be based abroad. There would be a significant difference with respect to the external environment between India and abroad. Thus, the results obtained would not be fully reliable.

h) Assessment on Reporting

Technology when introduced in reporting would reduce the time by about 80% of the original process. AI can remove a huge burden on the accountants by automating all the time consuming and repetitive process. They can give a real-time status of financial matters and can also process documents using natural language processing and computer vison by making the process a lot faster and inexpensive. Like the other departments the complex process and the briefing with the clients is inevitable without human interaction. Thus the constraints on complex problems remain.

i) Assessment on Investment

Technology can be used to read the earnings manuscripts, identifying non intuitive relationships between securities and market indicators, analyzing alternative data such as weather forecasts and container ship movements, monitoring search engines for words on specific topics to structure hedging strategies, using corporate website traffic to gauge future growth along with clients' behavioral patterns, to monitor for suspicious transactions, and trigger response protocols, to generate management reporting on-demand. Since investment is a crucial part for every organization, there should always be a supervised model with human interaction for better monitoring and also to the compliance to the regulations.

V. CONCLUSION

Thus, technology is no doubt the factor which going to make every industry evolve with time. Insurance industry especially is data rich. Advanced algorithms of AI can indeed make meaningful outcomes and help the industry move in the direction of innovation and enhanced operational efficiency. But, the way it stands in the insurance industry, complete adaptation and automation would not be possible for various reasons mentioned earlier. We saw how technology impacts in a lot of ways in the world of insurance. Thus, in order to go forward, the only way is to establish a synergy in integrating the technology and the human capital. Instead of looking for the places to eliminate human interaction, we must start looking for places where automation would lead to the increase of the efficiency of the process and the people involved. We must look into those areas for automation where we feel the human resources are not utilized to its fullest potential. In this way, we create a stable ecosystem in the world of insurance for adapting to the technological era in order to widen its horizons and boost its efficiency. Once these assessments are done, the company would have in place all the necessary action plans to introduce the new technology and the contingency plans for handling the down side risks. Thus it would ensure the smooth adoption to the change.

Thus, with the help of this proposed method, an insurance organization can get a better perspective about the various upside and the downside risks involved in adopting any new technology in its process. This aids the process of decision making and companies can take informed decision whether to implement the same or not. This methodology will not only catalyze the process of new technology implementation; it will also open several new avenues where new technology can be implemented in an insurance organization. Thus enhancing the overall operational efficiency of the insurance organization.

VI. ACKNOWLEDGMENT

The authors express their gratitude to the revered founder chancellor of Sri Sathya Sai Institute of Higher Learning, Bhagwan Sri Sathya Sai Baba.

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