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HYPERAUTOMATION IN TRANSFORMING UNDERWRITING OPERATION IN THE LIFE INSURANCE INDUSTRY

Aparajita Srivastava [1], Aditya Kumar [2], Madhavi Damle[3]

[1,3]Symbiosis Institute of Digital & Telecom Management,

Symbiosis International (Deemed University), Pune, India

[2] ACOE, AB InBev (Anheuser-Busch InBev), Bangalore, India

Email: [3]mdalme@sidtm.edu.in

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ABSTRACT

Today in the hyperconnected world, technologies like robotics process automation, machine learning, artificial intelligent, natural language processing, optical character recognition etc offers various automation opportunities for every industry. Particularly in insurance industry, automation can stand up to being the game changer.

Underwriting operation still rely heavily on experience and labour-intensive processes facing new and increasing risk, disparate systems consuming time, enormous effort to assess increasing volumes of data. Against this backdrop of inefficiency, the underwriter's job is getting harder, complex risks are emerging around cyber protection, natural catastrophes and fraud. At the same time distributor brokers are demanding that underwriters quote more quickly, more often. The rationale of this conceptual paper is to propose a model that outline a way for life insurance underwriting software procedure to optimize and simplify the customer acquisition process by quoting personalized premium. The paper also touches upon cost benefit, and cases of similar implementation. The model demonstrates the application of intelligent processing, intelligent monitoring, intelligent assessment using various automation capabilities. The study aims to provide an end to end automatic system to underwriting operation without human interference, overcoming the shortfall of current model.

1. Introduction

The process of underwriting determines life insurance premium. Various factors are considered for quoting a premium. Risk assessment is done considering age, medical history, claims history, marital status, driving record, family medical history, gender, hobbies, lifestyle, credit history, job, health, smoking status, and area of residence (Howard, 2012).

Every insurer determines risk differently, there is no methodology or standard formula as such (University). The insurer determines the risk of death in the process. A 60-year-old person will be charged higher than a 20-year-old person. It will be also determined on the basis of probability of illness, existing diseases etc. After coming to the base price additional operational cost and profit margins are added. Operational cost like the insurance agent's commission, the cost of policy document, and other overhead expenses of the insurer (Williams, 2010). Apart from these charges some insurer even tends to charge contingency cost meaning number of claims in a year cannot be estimated by insurer hence a contingency cost is added as safety. This way insurer adds investment and financial stability to the company. In this paper we attempt to align this process with Hyperautomation, which comprises of AI, ML and other intelligent algorithms

Underwriting in insurance is ripe for automation. It involves gathering and analysing structured, unstructured or mixed formats information from various sources to determine risks associated. It is a very prolong and tedious process which takes around 3-4 weeks to complete on an average in life insurance niche (Howard, 2012). Because of such a long process around millions of people drop out in between. Hyperautomation has got capabilities to automate the most-time consuming insurance operations. The long-term impact of automating underwriting process is to provide customized products based on individual preferences.

The study is to propose a model for intelligent processing, intelligent monitoring, intelligent enablement to ease the labour-intensive job, risks, volume of data and efforts in underwriting operations in deciding life insurance premium. This model is intended to provide a foundation of standard content that can be used for discussions in the industry. This is focused on the Underwriting process of life insurance policy, and it is anticipated that some of the content need to be customized according to business use cases.

The flow of the paper is as follows- firstly it explains the underwriting process in life insurance, contract making for life insurance policy, overview of manual underwriting process, Intelligent Automation or hyperautomation, The latter half of the section talks about a general understanding of technologies disrupting in life insurers, a theoretical framework or a model build to bridge the gap with advanced technologies to enable automation, value levers, cost benefit and lastly few cases of similar implementation.

2. Literature Review

2.1 Understanding of underwriting processes in life insurance

According to Wuppermann (Wuppermann, 2016), the process of underwriting involves gathering information of various types from the applicant, which is labour intensive job and tedious. Applicants are prescribed to undergo health check-up and asked to submit all relevant files to the insurance provider. Manually collecting medical records are tiresome and prone to errors. Records can be plurality being gathered from disparate locations, as rightly pointed out by (Jensen, 2014). Then, the underwriter analyses the profile to accurately determine risk associated and conclude if the application can be proceeded to further process. Subsequently, premiums are calculated (Prince, 2016). On average, it takes at least 30 days for the application to be processed. During the period the insurance company has a chance of losing customer. People are reluctant to buy slow-moving services. Because of the lengthy and time-consuming underwriting process, customers switch to competition or choose to avoid purchasing life insurance policies. Lack of proper writing can lead to dissatisfaction with customers and a decrease in sales policy.

Life insurance policy can be brought from several options however whole life insurance and term life insurance are the major ones. In term life insurance, if a person dies within the term then a predestined amount is paid to the beneficiary. Term insurance policies are the most affordable out of all. The policy expires at the end of the term. On contrary, whole life insurance is contemplated as a permanent life insurance policy as there is no expiry. Death benefit is given with some cash value to beneficially. A person earns interest on that cash value as well as death benefit in this. This is more expensive and complex. Quotation is quicker for term insurance than for whole life insurance.

2.2 Making for Life Insurance Policy

A study by Mamun (Mamun DMZ, 2016), dictates that less efficient underwriting capabilities causes a major operational failure for the insurance companies as survey in Bangladesh. Another threat to the life insurance businesses is that they can witness adverse selection. Wrong selection refers to a situation in which a complete and honest information is not there with applicant, and the person ends up giving policies in high-risk (Harri T, 2014) . Thus, the firm with skilled and competent underwriters reduces possible losses of the company. Specifically, insurers avoid making wrong choices as it has direct impact on the business's growth and profitability (Stratmann, 2015). Adverse selections can be mitigated if risk assessment is done by correctly classifying the risk levels of incoming applications of individuals using analytics.

Stating an importance of advanced technology and predictive modelling, (Jayabalan, 2018) said that with right analytical solutions, the work can be done quicker and greater results can be achieved. The utilization of Big Data encourages new social, granular data assortment and empowers administration personalisation. Telematics has lessened related dangers but made way for new ones, for example, digital dangers. Comparison stages present clients with a thorough decision of a wide range of insurance covers and for some situation permit to purchase insurance on the web. Quick data and Big Data permit more predictive and evaluated analytics. Better division is driven by more prominent preparing capacities. Telematics gives prompt data which can assist safety net providers with more precise cases evaluation and diminish extortion. Innovation to diminish preparing time. (Cappiello, 2018)

3. Objectives

1. To obtain the understanding of underwriting processes in contract making for life insurance policy
2. To obtain an overview of hyperautomation/ intelligent automation (RPA, ML, AI)
3. To explore the opportunities of automated/intelligent solution in policy making for individuals
4. To propose a model and present an initial cost analysis for implementation
5. To evaluate cases of similar implementation using SWOT analysis

4. Methodology

This is a concept paper to suggest a model for hyperautomation of Life Insurance Underwriting process. The technique included Secondary Research as this field is a KPO field and needs complex, highly skilled decision sets.
The secondary information was collected from online resources and other researches to build upon this conceptual model with plugging the gaps found in life insurance domain in present day processes.
The challenges with strengths, weakness, opportunity of the automation enabling software are discussed. Various forms of information were taken from various websites, reports, press release, social media sites, journals, articles etc. to correctly understand the positioning of the software and applications.
This research also focuses on the value added with Costs benefit analysis and used cases to understand of similar implementation which are yet not efficient projects. These comprise debate about the profit, sales were taken into account to understand the acceptance of software in industries.
After a deep-dive analysis an idea/model was proposed which is 100% machine driven as a concept Model.

5. Overview of manual underwriting process

Conventionally, underwriter's job is under continuous pressure. As a part of his normal routine underwriter get request for evaluating client's exposure to risk and quote a premium for the policy. He gathers the information, evaluate based on his knowledge and experience. Clients are contacted back in case of additional information. He classifies customers based on the similarity. He takes necessary guidance from senior underwriter. Uses actuarial table to classify/rate customer based on their vulnerability to risks. A proposal is then proposed to customers with other necessary information. In case of dissatisfaction shown by clients on premium price they negotiate. Profit and solvency concern forced insurance companies to relook at their underwriting operation under IRDA regulation on — “File & Use” system.

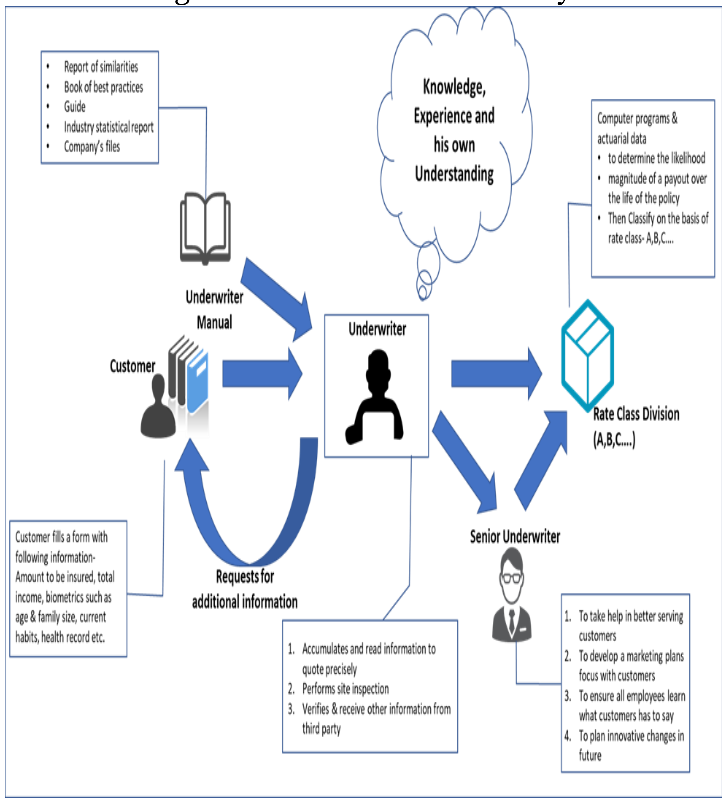

Figure 1: Traditional Underwriting Process (Source: Author’s own)

6. Intelligent automation or hyperautomation

Hyperautomation is moving from fixed automation to perception-based processes. RPA augmented with AI and ML becomes the core enabling technology of hyperautomation. Combining RPA and AI technologies offers the power and flexibility to automate where automation was never possible before. This makes system self-sufficient, self-healing and beyond automating tasks.

6.1 Robotics Process Automations (RPA)

This is process of automating the tasks or processes with the help of robots or software. The rule-based process defined by the user programmed to use machine learning capabilities to suggest recommendations. RPA is best suited to replace processes owned and operated by redundant, monotonous, business operations to reducing cost, improving efficiency by enhancing scalability and flexibility, employee satisfaction, customer satisfaction, replaces the need for IT system change management, audits ability and consistency.

6.2 Artificial Intelligence (AI)

AI is the study of intellectual capacities using computational knowledge. It includes machines that have the capacity to perform any intellectual tasks, liberating people from everyday undertakings. The strong processing units that enable high-level computations with understanding, thinking and reasoning skills. Many human mental activities can be performed by machines like doing mathematics, engaging in common sense reasoning, understanding language, making machine perform tasks, or even automated driving.

6.3 Cognitive computing

A cognitive computing refers to the computer intelligence modelled by human brains. That possess natural language processing capability, get trained from episodes, associate with people in a natural way and help in deciding (noor, 2014). A cognitive system gets trained with more incoming data, learn more from human interactions, and not with hard core programming. Cognitive computing overlaps with Artificial Intelligence and similar technologies to build cognitive applications. These system work as support systems with better algorithms to provide smart insights (noor, 2014). They use data mining/text mining pattern recognition, natural language processing to interpret how human brains work.

6.4 Machine Language (ML)

ML is a subset of AI which use statistical methods/models to enable machine itself generate data-driven decisions execute tasks. With the increasing number of data these machines are programmed with such algorithms that they can self-learn and become mature with time. According to (Alpaydin, 2020), Machine Learning utilizes the hypothesis of insights in building scientific models, on the grounds that the center undertaking is making inferences from an example.

6.5 Language Understanding Intelligent Service (LUIS)

LUIS is a Natural Language Understanding system that is extensively used to apply the important concepts of entity extraction and intent classification.
It is difficult to communicate with computer in binary code therefore, artificial programming language was created to communicate with computer. The text retrieval systems store texts and produce a query to retrieve the content from the archive base. Another approach is a statistical approach called keyword-based system. In this approach, a logical/Boolean expression consists of a keyword, these keywords are used in querying database. This way approaches a directory with keyword in the document database (Stabler, 1997). Microsoft Azure has given a cognitive service. Utilizing this administration, we can utilize REST APIs to extract valuable data in particular 'plan', 'entity', 'phrases' and so on from any sentence.

6.6 Optical Character Recognition (OCR)–

OCR is a software that reads a photo scanned copy, and coverts it into text file for further editing. In OCR, writer writes generally on paper by using marker of different brightness. The contrast is acquired optically through scanner or camera and a 2D image is formed. (Singh, 2013)

7. Technological features disrupting life insurers

Digital Labour- It is a software working as a human, or mimics the way humans make decisions. Focussed on the automation it encompasses machine learning, RPA, and other cognitive technologies for making system knowledgeable, flexible, and more powerful. (eric brjynjolfsson, 2011)

Behaviour- driven – this is to consider attitude, mental stability, psychological status, social media happenings etc. that help make pricing more feasible and improve risk assessment. (Brindle, 2017)

Data Analytics- It encompasses new technologies that analyse raw data, find patterns to drive insights, and make system more intelligent through continuous learning. (Boobier, 2016)

8. Model

Optimizing the underwriting operating model by building winning solution for quoting and on boarding customers. Intelligent evolution uncovers the use of intelligent automation to support Underwriters processing & preparation, supplementing workflow with Intelligent Enablement to support and drive decisions, use of third-party data and advanced data techniques to improve data quality and supplement information. The automation's scope of building rule-based workflows to change to knowledge/smart machine work, with greater return on investment. The range of tools will enable dynamic experiences. The agile nature of organization's work processes can be met by quickly reconfiguring processes. The fundamental need to build the project is the skilled people with in-dept understanding of every component. Understanding the logic will help understand the capability and feasibility of system.

In the model below, a range of capabilities are used to gather information, then specific data are extracted in structures from digital files at scale – removing the need for manual efforts in data reading and entry. This powerful engine makes data more accessible and actionable and uses data-driven analytics to gain more insights into customer behaviour.

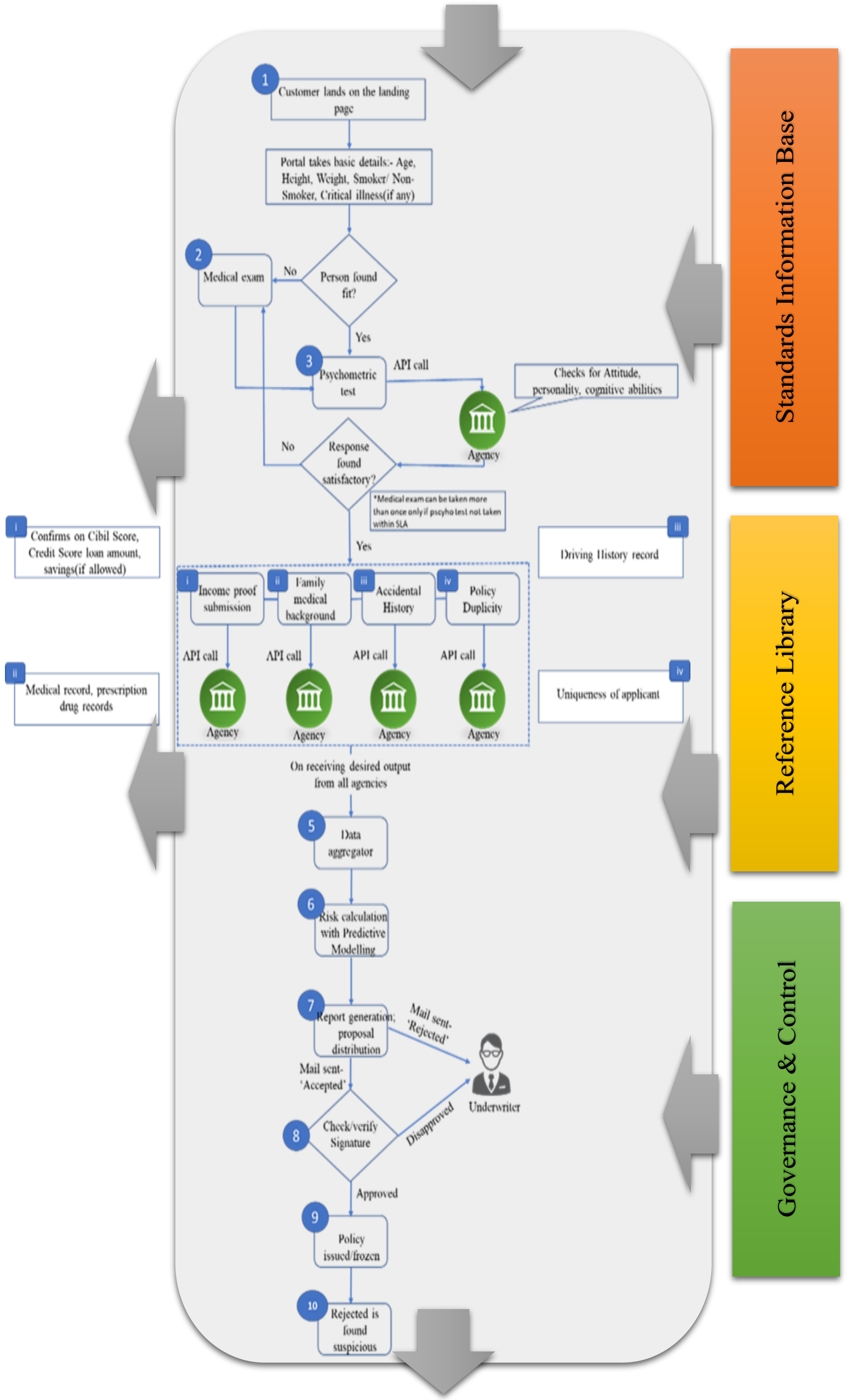

Figure 2: Hyperautomated Underwriting process (Source: Author's own)

The flow diagram depicts the model that is as follows-

1. As soon as the customer lands on to landing page, virtual assistance a digital bot takes basic information like age, weight, height, smoking habit and critical illness. BMI is internally calculated. If the person is smoker, has high BMI or has any critical illness he is asked to visit physician for tests.
2. The physician will run a series of tests (required once), fill in a form based on the report generated from diagnosis and send it back to the insurer. Few insurers borne the cost of diagnosis, which is subjected to companies' policies. In case the person is fit, he is then routed to next chat bot which does his psychometric test.
3. The psychometric test can act as an attitude checker and a lie detector. Either emotional recognized sensor can do the job or an API call could be made to agency to testify his responses. If he is a sad personality or mentally unstable his premium is likely to go high, if the person seems motivated or is involved in physical activity then his premium is likely to be low.

Machine Learning compares the input with previous fed data and does the analysis. For instance, if the person is 40+ and a rally driver then his premium will be higher. Machine Learning helps uncover pattern of similar traits people. However artificial Intelligence predicts his health condition in future based on his area of residence, kind of job etc.

4. If his psychometric test is cleared without any suspicion then he is made to fill a form asking for following details –income proof (PAN detail, etc), Parental illness, accidental history and policy duplicity. An API call is made to agencies to verify the responses. Agencies can either ask for customer's inputs to suggest true/false or send correct result of the person (subjected to policies of the agencies and insurer)

Until now was block1. Block 1 is a cognitive engine that includes chatbot, ML, AI, also LUIS. LUIS is an engine with NPL technology. Natural Language Processing can also be used to read intend of the customer through his subjective answers. Once the intents are identified, the solution can be trained to handle conversations for those intents. In case his intentions are not seemed to be normal he will still be directed to further process but his premium will be little higher. As we proceed down the flowchart, in the background recorded data will be filled in an excel sheet under designated row which will be ultimately served to data aggregator.

5. On receiving green signal from all agencies data aggregator will learn and prepare a report to run a model for better insights. Data aggregator is the compilation of all the responses received until now and present it in a summarized format to run a suitable model for insights. Roll-up or summary tools reports all the relevant data in certain format. This also reduces overall dataset and makes it easy to serve it to predictive model for analysis.
6. For risk assessment predictive analytics and prescriptive analytics can work together to mine data, discover patterns and recommend predicted outcomes. The model can classify customer (on the basis of job type, health type, default category etc), forecast (how long will the person live), identify

anomaly (claim fraudulent, etc), cluster formation, and lastly time series (future premium received vs insurance claimed amount).

7. After analysis, RPA will run a bot to create a proposal based on the output from modelling. This proposal will then be automatically sent to customer through email. He has to sign/stamp, scan and email the response back to the same email id.

8. The signature is verified through Optical Character Recognition. OCR checks the signature authenticity either with the previous employer, or from any government issued ID card. In case he objects to the proposal made, underwriter manually decide on taking the next call.

9. After his signature is authenticated, policy is issued or froze.

10. If the person is found suspicious in one month of holding time then further action is decided by underwriter.

A trained individual cannot cover all the possible cases and variations of an application. Machine helps overcome this. Decision making time gets drastically improved, a lot of human effort and cost involved can be saved, customer can fill in responses according to availability. The biggest advantage is saving server space and cost. The telematic system used to store the complete call in server, now with this system server costing can be saved as the complete information can be stored in a row of designated SQL table.

The model presented is aligned with best practices adopted by enterprise. Author has taken reference from models adopted by enterprise as best practices. Standards are complied with business standards, data standards, application standard, technology standard to avoid unambiguous basis for architectural governance. Requirements repository to record and manage all information relevant. Governance log is to provide compliance record for stakeholders.

Note: As the system is designed to work 24*7, the SLA for completion can be set to 10days. In situation where a person takes psychometric test after 10days or more, based on psychometric report if needed, he has to undergo medical test again.

9. Underwriting intelligent automation other value levers-

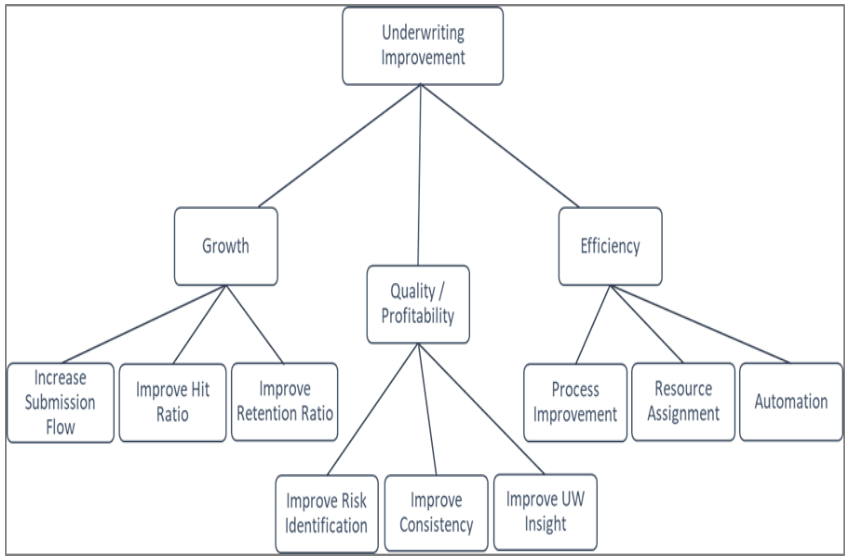

Figure 3: Value Levers

Source: Author's own

UW improvement value levers include profitable growth, quality / profitability and efficiency. The solution captures underwriting data from customers on various parameters, organizes them in an easily digestible way for the underwriters leveraging scraping bots and Artificial Intelligence technologies. Various values include reformulation of UW job by intelligent targeting, speed to quote, and high retention probability. Risk exposure is smartly measured. Data movement is recorded rightly to improve consistency. Comparative analytics and data visualization improve UW insights. 24*7 working system ensure data collection based on suitability. Intelligent views of information to support processing. UW enablers naming RPA, analytics, AI/ML makes intelligent assessment easy and automate tasks. The intake manager no longer needs to spend time in gathering all information from disparate sources. Underwriter will no longer spend time on data preparation and thus the system will proof to be profitable

10. Cost benefit-

Businesses can benefit immensely from hyper automation. Helping insurers cut costs, manage risk and drive growth, evolve through digital innovation, platform modernization, and improved distribution & marketing.

The system was built by keeping following costs benefit in mind: - RPA can reduce the processing costs up to 80%, minimize rework costs and automate mundane work to free human resource cost on those areas. With every new commers coming in the initial costs or expenses of the project (front-loaded) to go low. Operating costs can be optimized with following features: - i) loss reductions at new business stage ii) servicing costs per policy iii) % of queries resolved by self-service iv) lower % of rework. With software in place need of assets and risk associated goes low. By minimizing assets, the system ensures i) no dependency on inbound flow ii) customer ease by building 24*7 working window iii) no employee liability iv) customer retention will impact revenue v) reduction in yearly spending. (Bender, 2015)

Value generated will lead insurance companies to increase their profits by reducing their costs, increasing underwriting capabilities, and also through the reduction of administrative costs and general expenses.

11. Cases of similar implementation

11.1 Use case 1: KPMG

KPMG helps insurers by automating underwriting using a framework-based approach. The model eases the burden on underwriters by coordinating an assortment of rising innovations that pave path to new information sources empowered by IOT, empowers advanced work, break down client social information and set up computerized channels for constant arrangements. Unified platforms, effective communications, and ongoing visibility into the process help underwriters/agents work collaboratively.

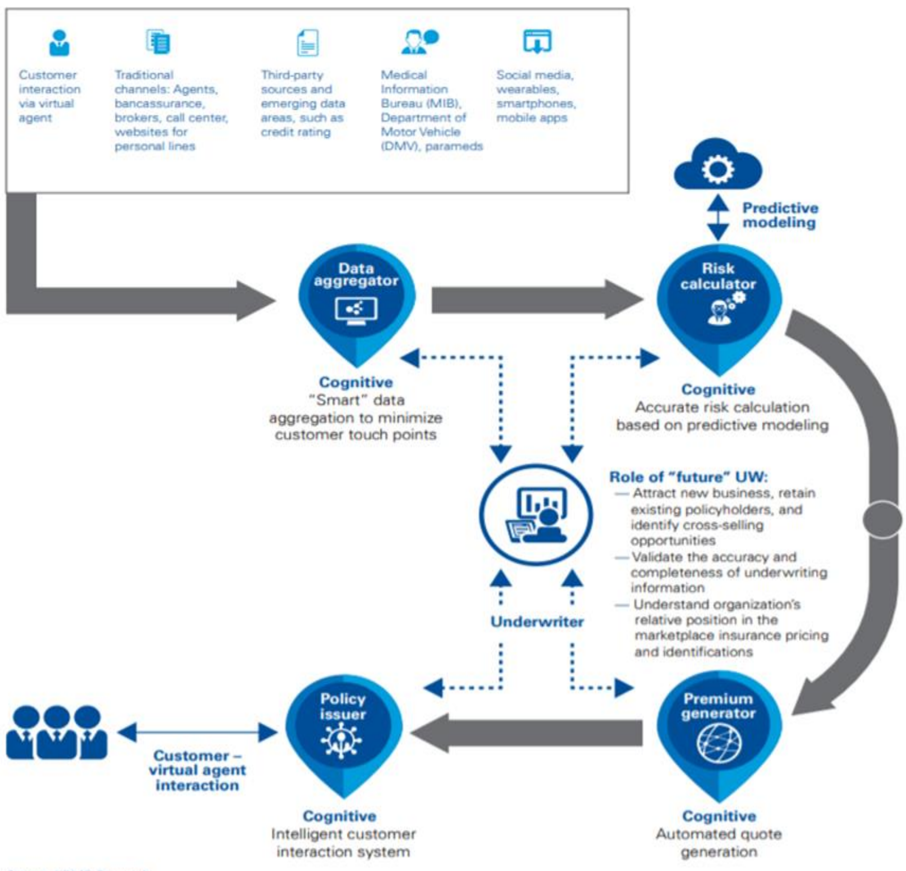

Figure 4:KPMG Underwriting process

Source: KPMG

Benefits: The data collected via IOT, wearables/connected devices, social media etc. can be made available anytime. With robust technologies financiers will have the option to perform more exact and more educated risk assessments in a small amount of time. The spare capacity of the underwriting resources can be used in recognizing cross-selling chances, procure new organizations, hold existing policyholders, and increment endorsing benefits while looking after market competitiveness.

Drawbacks: There always be question about privacy issues. Access to private information or buying data from agencies are restricted in some countries. High risk of fallacy information from emerging data sources areas and inefficiency of cross checking. No proven measure to verify if the person has already applied for one such policy in the recent past. The plan cannot be put to immediate use due to lack of IOT sensors in India.

11.2 Use Cases: EY

EY has built digital underwriting with incredible human-machine interactions. EY has assembled advanced underwriters with the incredible human-machine associations. Advanced underwriting doesn't compare to human-free underwriter. As nonsensical as this may sound but human ability will be a higher priority than at any other time. The best underwriting associations will empower the power of innovation and ability. Utmost machines can give procedure automation and decision help, but experienced underwriters will develop their multifaceted jobs and learn to expand their market significance, singular brands and leaderships. The aim is to make underwriters master of all trades with just one click away access to data, analytics, and many more.

Sales executives:	growing the book of business, increasing retention rates, building relationships, lead generation and prospecting
Data scientists:	data-driven decision-making at the account and portfolio levels, risk insight, profitability analysis, predictive modeling for pricing and risk evaluation
Customer advocates:	improving the customer and agent experience, coordinating account services (loss control, claims, education) to strengthen customer loyalty and improve risk performance
Innovators:	creative problem solving, new product and service development

Figure 5: EY Underwriting Process

Source: EY

Benefits:

Human machine interface (HMI) improves the efficiency of a task that is being performed. HMI can reduce hardware costs like panels, cables etc. An operator can see the schematics of the system and use stored data for troubleshooting and fixes. Clients can interact with human support and get answer to n numbers of issues. Human can efficiently connect with emotions of human which will be beneficial in sales lead generations.

Drawbacks:

A flawed HMI software system can pose a high risk of hacking. Hackers can crash systems that may lead to loss of important security and confidential data.

Might take longer time to process. Information gathering from individuals on call according to convenient time can make process slow. Operational cost can go high and return on investment might not be safe.

11.3 Findings of Case study

Big players in the industries aims for encouraging vision including more noteworthy worth creation for the organization dependent on growing roles, different abilities and an amazing human-machine blend for underwriting processes. Companies believe more benefits are in marrying needs of matured technologies like big data capabilities, RPA, analytics, automated portfolio management, underwriting merchandizing principles, with emerging technologies like blockchain, sensor-based, AI, ML, image and video analytics. A well-defined road map navigates to a successful digital underwriting transformation.

KPMG's solution is expected to drive resource utilization improvement and productivity by deploying platforms for better work orchestration, self-functioning workflows etc. However, the issues lie with privacy. There are immense opportunities for KPMG's but can be under threat if regulation changes from government side. EY's solution of human + machine talent is well equipped to be a benefit plan advisor, virtual assistance, intelligent case advisor, intelligent contract advisor etc. The problem that adds on to this is human expert knowledge is imprecise, anecdotal, or uncertain. Even though the solution is going to be intelligent with human touch, warning comes with change in SME (subject matter expert), or mindset of person at the decision time.

12. Findings

We established a reliable, focused underwriter process with feedback system to maintain credibility of the solution. The automated solution in insurance underwriting process is expected to drive over 10-20% productivity ensuring lower response time and better accuracy.

The model is designed considering necessary parameters. Psychological test is the key to understand psychology of customer in his/her likeliness to die/commit suicide. Bot automatically drops and prescribes a physical test, if the customer is found to be a liar. In case he is found to have depression, anxiety etc as his nature from the test's report then machine will automatically push premium price higher. The need of human visiting client's home to learn about personality is taken over with this. With mitigation of telematics to take information, the cost of server space is saved. The overall record can be saved in a row of SQL server designated table imitating the traditional way of keeping complete call record stored in server. Predictive model uses statistics to predict outcomes by performing a comparative analysis of one customer's account to other similar accounts, then discover the impact. Enhanced analytics reduces ambiguity in decision making. In some case, if 2 people A and B have

all the data from top to bottom same except for the fact that A is found to be mentally depress and B is not then premium price will differ according.
However, the implementation of the system requires guidelines changes based on company's internal policy, require certain skillset to switch the application process from paper-based to digital, changing the business process, automating the creation of reports/proposal and notification letters. The innovation agenda is to scale vision by combining intelligent technologies and insurance talents with next generation skills. Improve decision making by using the right resource at the right time.

13. Discussion:

The purpose of this research was to explore the usage of RPA, AI and its subsets in developing Hyperautomated system to handle large amount of uncertain data in quoting unbiased premium price for customer applying for life insurance policy. In real life, the nature of information that underwriters' collects are unstructured which require him to do lot of manual work under restricted timeline which puts enormous pressure on him. In the proposed work the risk assessment is evaluated using peripheral automation technology like- LUIS, RPA bots, Machine Learning, Optical Character Recognition to generate suitable pricing to maximize conversions. Other benefits of this includes improvement in risk assessment and portfolio management, personalized pricing, accelerates quotation process. With machine overtaking human businesses, human resources can be utilized in growing business in new locations and markets with innovative ideas.
Amidst several benefits there could be strategic challenges in implementing hyperautomation like finding right people with the right skills, proper understanding of business processes, human resources insecurities, mistakes of calculating ROI, lack of governance, failure to own post-implementation tasks. Business might face resistances like the ones mentioned but can overcome through strategic planning. Insurer must hire right set of people, insecurities of robots "stealing" human jobs must be catered with other similar organizational culture problems. Qualitative factors must be converted into quantitative factors like employee engagement, customer satisfaction for calculating ROI for keeping an eye on the numbers. A product can be designed through trial and error, which is bit lengthy and costly process and business suitability must be checked.

14. Conclusion

The end-to-end automation in underwriter's job can be very successful in insurance industry. The cognitive engine with its AI and RPA components to enable this success.
The future of underwriter deals with integration of range of software. This study deals with evaluation of automated underwriting systems with an emphasis on deep learning of system for building smartest process. The goal of automated underwriting is to optimize performance and increase profit by enabling personalized prices for customers. The existing studies till now have

been focusing either on human-machine parallel interactions, or an automated system considering social media, wearables datum etc. but not much considering mental health. Advancements in devices with several technologies allow access to information. Sometimes, every information available does not work in favor but destroy minds leading to depression, anxiety and several disorders. Simultaneously increasing the risk of death. Check on mental state, psychologically stability still takes the back side in risk assessment in insurance industry. That's a loophole this study understands. Thus, this study contributes. Finally, as per author's perspective, the transformation in underwriting is asking for Digital transformation, without human touch just like other segments in the industry. This model helps system consider aspects necessary for this generation. The system is based on iterative approach and is subjected to observation and therefore susceptible to modifications.

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