**Examining AI's position in automation of insurance underwriting and its impact on the future of life Underwriting**

**A case study of Sanlam Insurance**

**BY**

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**A RESEARCH REPORT SUBMITTED TO THE COLLEGE OF COMPUTING AND INFORMATION SCIENCES IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE AWARD OF A BACHELOR’S OF SCIENCE IN SOFTWARE ENGINEERING**

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# Abstract

A generation of internet shoppers who are accustomed to researching, purchasing, and evaluating items has joined the insurance industry, yet they are met with a purchasing experience that falls short of their expectations as "digital natives". As a result, the industry is always looking for new ways to fully underwrite individual applicants in less intrusive, cost- and time-effective ways. In order to enhance customer experience, technology has rightly been seen as a major part of the solution to the challenges facing the insurance industry. Risk prediction, which is central to enhancing efficiency, alleviating cost pressures, improving insights and reporting and delivering a superior customer experience, has been a major part which insurance companies have transformed by introducing Machine learning and AI models to solve the challenges that have been faced for over decades ago. These emergent classes of ‘insurtech’ are the latest iteration of what has been a fairly lengthy evolution towards a greater digitization as human judgement has been replaced by a more mathematical and scientific approach. While several papers about automation of insurance have been published, extant research has not quite caught up on the use of AI in the automation and augmentation of insurance specifically life Insurance. This paper therefore will examine AI’s position in automation of insurance underwriting and how that role may affect the future of life underwriting

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# Introduction

The process through which an insurance firm evaluates its risk is known as underwriting[1]. It aids an insurance company in deciding whether or not providing coverage to an individual or business is profitable. In order to provide coverage, an insurance company must be able to estimate the risk involved[2]. It must also be aware of the chances of something going wrong and having to pay a claim. Life insurance is similar to any other company in many respects. Efficiency in operations, delighted consumers, and stable profit margins are all critical to success[3], [4]. A generation of internet shoppers who are accustomed to researching, purchasing, and evaluating items has joined the insurance industry, yet they are met with a purchasing experience that falls short of their expectations as "digital natives" [2-3]. As a result, the industry is always looking for new ways to fully underwrite individual applicants in less intrusive, cost- and time-effective ways. Technology is seen as a solution by many life insurance businesses. A flood of sophisticated tools has reached the market, many of which use artificial intelligence (AI) approaches such as machine learning to make decisions[6].

The continuity of data is one of the most fascinating and irritating issues in underwriting. Practitioners have long understood that having timely access to the relevant data sources will help them make better decisions[7]. To be clear, insurers have already heard enough about the importance of making more "data-driven" decisions[4], [8], and their underwriters appear to have data. It is, however, frequently delivered in the form of static monthly or quarterly reports. Underwriters can't afford to wait in expectation of future narrower margins and a softer market.

Another challenge for insurance buyers and brokers is having to invest time in time-consuming underwriting processes, especially when the carrier does not appear to know what it wants to underwrite[9]. Agents and brokers became significantly more choosy in the early days of the pandemic, demonstrating this. When visiting clients in person became less appealing, they grew more selective, and calls that were unlikely to offer value swiftly shifted online. This is a result of most industries' shift to virtual work methods, and it reveals an inconvenient truth: both commercial and retail clients dislike the insurance buying process, and they dislike it much more if the underwriting process is inefficient.

Although insurance companies have embraced technology solutions such as rules-based engines and machine learning-based underwriting software to solve some of these issues[10], [11], they still fall short of entirely addressing the industry's problems. This study will look at AI in automation of insurance underwriting, with a focus on life insurance, utilizing Sanlam Insurance Company as a case study.

## Definition of key terms

**Artificial Intelligence** - Artificial Intelligence (AI) is a part of the computer science that is finding ways to develop predictive models for machine learning[12]. This is the essence of AI, so that it can be implemented in the computational decision-making process. From analysis of data-pools, algorithms that are based on predictive modelling are designed. The goal is to achieve the best possible outcome and solution for any given task. Predictive models are being used to develop “the intelligent system”, with the goal of absolute computational rationality and cognitive reasoning.

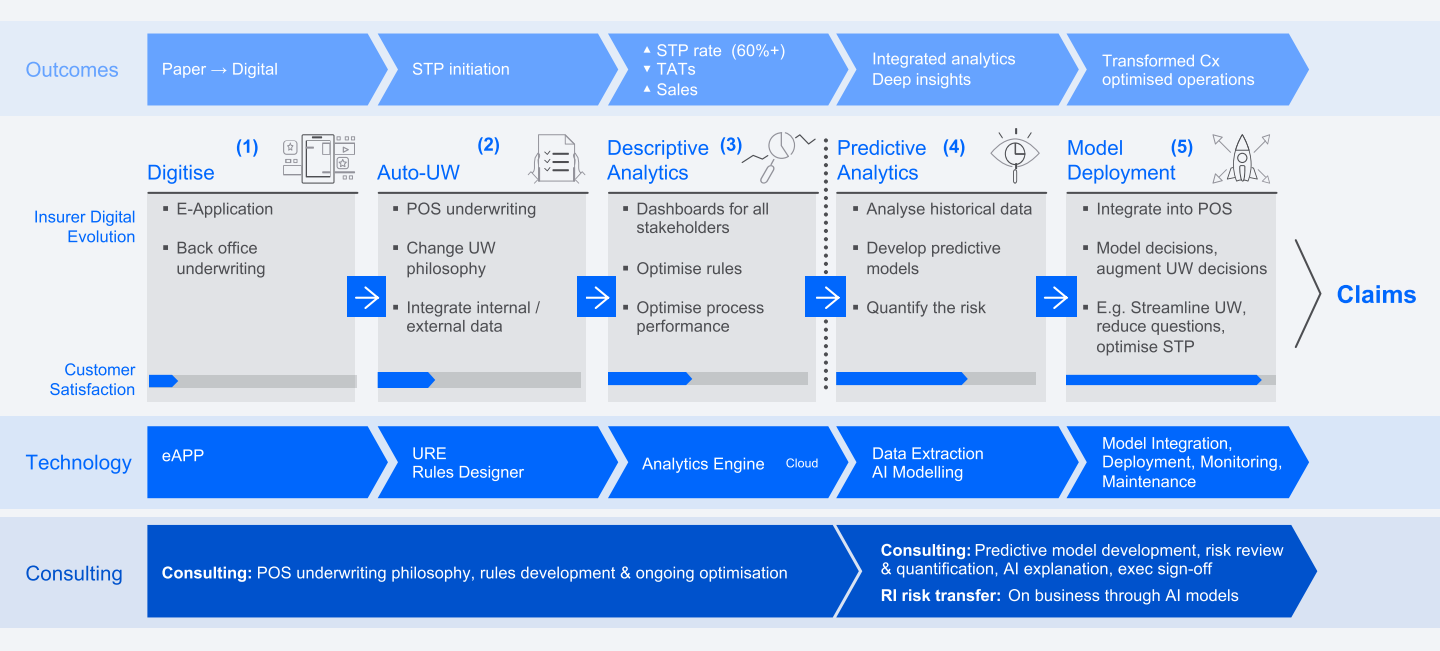
# Literature Review

## Introduction

In order to enhance customer experience, technology has rightly been seen as a major part of the solution to the challenges facing the insurance industry [4]. Risk prediction, which is central to enhancing efficiency, alleviating cost pressures, improving insights and reporting and delivering a superior customer experience, has been a major part which insurance companies have transformed by introducing Machine learning and AI models to solve the challenges that have been faced for over decades ago[2]. These emergent classes of ‘insurtech’ are the latest iteration of what has been a fairly lengthy evolution towards a greater digitization as human judgement has been replaced by a more mathematical and scientific approach. While several papers about automation of insurance have been published, extant research has not quite caught up on the use of AI in the automation and augmentation of insurance specifically life Insurance[1], [13], [14]. This paper therefore will examine AI’s position in automation of insurance underwriting and how that role may affect the future of life underwriting.

## Theoretical Review.

Insurers digitized their systems and implemented jet casing systems for online and back-office models. These systems were often developed inhouse and intended to introduce some automated capabilities to the underwriting process[15]. The next iteration of systems gave underwriters the opportunity to review and amend their own underwriting philosophy by introducing behavioral economics and external data [8] but in most cases, they still required IT and programming expertise. Maier Marc and Carlotto Hayley point out that these classes of systems are sufficient to the industry but are coarse and subject to inconsistency[6]. As a result traditional underwriting limits the degree to which an insurer can estimate risk from data and offer efficiently priced products[6, 13]. With the rise in data availability, insurers were now able to offer descriptive analytical power via insights from dashboards and reports [16]. This was a giant leap forward. All risk-based decisions hinge on making connections between various data points and identifying patterns within them[13], [17]; however, these patterns aren’t immediately discernable by humans. This lead to rise of Machine learning and AI in the insurance industry, Advanced analytics could reveal these previously hidden connections and relationships with an exceptional degree of accuracy. The majority of life insurance businesses use second or third- generation systems. However, the evolution is continuing. The fourth stage is where insurers are now able to obtain deeper insights from their data, using advanced analytics techniques, and developing predictive models that can further improve the customer experience, increase sales and enhance business performance[10, 11, 18].

Figure 2‑1 The Digital Roadmap of Insurance Underwriting

In light of these evolutions in the insurance industry, several researchers have become increasingly interested in the application of AI and Machine learning in insurance underwriting. Maier Marc and Carlotto concluded that “*pairing Machine Learning capabilities with historical data provides unprecedented opportunity in the life insurance industry to transform the underwriting status quo*”[6]. Boodhun, Noorhannah [2] further points out that predictive modeling using learning algorithms can provide notable differences in the way business is done. Previously, risk assessment for life underwriting was conducted using complex actuarial formulas and usually was a very lengthy process. Now, with data analytical solutions, the work can be done faster and with better results [2, 4, 15].

Several empirical studies have focused on the application and deployment of different machine learning in the underwriting systems to boost their efficiency and speed up the whole underwriting process. Indeed a systematic review by Meystre, S. M. [7] confirmed that performance increased by 90% after a Natural Processing Algorithm to extract text from medical documents was employed in the underwriting system. Nonetheless, it wasn’t without its challenges because most underwriting systems are statistically-based and therefore required annotated corpora for training. This presented a research gap that this paper addresses. This paper will examine the position of AI in automation insurance underwriting and its impact on the future of life underwriting.

# Research Methodology

## Research design.

The researcher used quantitative research design to collect data in order to test hypothesis, to answer questions concerning the current status of the subjects under the study. The quantitative approach was used because it allows the results to be presented by using simple statistics, tables, percentages and frequency distributions. Both qualitative and quantitative techniques were used to carry out the study.

### Study area and population

The study used a case study of Sanlam Insurance. A case study was more appropriate since knowledge is unique to an organization and because the company is a life insurance company hence the most reliable place for collection of the required data with ease as per the study. The study comprised of human resource, the underwriting department and Insurance agents. The target population was chosen because it was fully equipped with the information about the study topic.

### Sampling Design / Technique

Stratified sampling design was used to select the respondents because it is often administratively convenient to stratify a sample where a particular age-group or ethnic group, or employees of Sanlam Insurance were considered. It also ensured better coverage of the population than simple random sampling.

### Sample size.

The researcher used purposive sampling and simple random sampling to select up to 25 respondents. Purposive sampling was used to select respondents based on their experience, knowledge and interaction with all departments in life Insurance while simple random sampling was used because all the respondents were known and listed.

|  |  |  |
| --- | --- | --- |
| **Categories** | **Population** | **Sample Size** |
| HR | 3 | 2 |
| Actuarial department | 15 | 13 |
| Insurance Agents | 20 | 10 |
| Total | 43 | 25 |

Table 3‑1 A summary of the population categories and sampling criteria

## Data sources.

The researcher used both primary and secondary sources to collect data.

### Primary source.

Primary data was raw data collected from respondents from the field of the study using online administered questionnaires and a collective interview. This source was important because it enabled the researcher to focus on specific issues and enabled the researcher to have a higher level of control over how the information was collected.

### Secondary source.

Secondary data was obtained from reviewing literature related to the study variables and objectives from journals, newspapers, any statistical information that reflects Automated and Augmented Insurance Underwriting.

Another secondary source was online databases that have datasets relating to life insurance variables. Prudential Life Insurance dataset was chosen specifically because it had attributes that are suitable for life insurance. This additional information was very important because it validated and complemented the primary data from the study and had always been saving time.

## Data collection methods

The researcher administered data collection by using two instruments i.e., questionnaires and face to face interviews as given below.

### Questionnaires.

The researcher used both open and closed ended questionnaires to gather information from the selected respondents. Questionnaires were used because they gave a chance to the respondents to give their own opinions; they are time sensitive and cheap.

### Interviews.

This is an oral or written method of gathering information; the researcher used a combination of face-to-face and phone interview to collect information relevant for the study. Face to face interview was used because it enabled the researcher to get first-hand information whereas phone interviews were used because they seemed cheaper to get first-hand information from underwriters who weren’t stationed in Kampala.

## Data collection instruments

### Questionnaires

**Underwriter’s Questionnaire:** This was made up of questions that were targeted to insurance agents. I had both closed and open-ended questions and it was delivered online through google forms

**Users’ Questionnaire**: This questionnaire was made up questions directed to the end user. The questionnaire’s goal was to understand the customer satisfaction level during insurance application process.

### Interview guide

This was made up of guiding questions to the study. It involved face to face interaction with the respondents through discussions. Interviews were also used on key respondents who were the underwriters and insurance agents.

## Limitations

**Cost;** Costs regarding this limitation included transport, airtime, internet, typing, printing and photocopying of relevant materials, was experienced, however the researcher mobilized some money by borrowing from relatives and friends and use it sparingly in order to curb cost constraints.

**Time;** The researcher experienced time constraints in data collection, analysis, interpretation of data and final presentation, however the researcher put time element into consideration and met all appointments agreed upon by respondents.

**Non-responses;** The researcher experienced a problem of non-response from respondents who were given questionnaires to fill, however the researcher had to assure the respondents that any information given was to be treated with maximum confidentiality.

## Data Analysis

Quantitative data from Sanlam Surveys and interviews were coded and analyzed in Google docs. Descriptive statistics were generated and results were presented as either percentages or counts in both graphical and table forms. For secondary data, exploratory data analysis was used using Jupiter notebook and Python to study and understand the variables that are used under life insurance underwriting. The primary data on the use of AI in insurance underwriting were backed with an empirical trend analysis [19]. Qualitative information was recorded and typed out in Microsoft Word and summarized thematically. Content analysis was then used in the analysis of qualitative data[9].

# Presentation and Discussion of Findings

The findings were grouped under two categories;

The use of AI in insurance underwriting. This was specifically targeting underwriters and actuaries.

How AI is improving user experience. This survey was targeting insureds/end-users.

## Social-demographic characteristics.

### Insurance Agents.

The social-demographics summarized in the table below include gender, age and residence of the respondents. From the table we can see that 64% are male whereas the remaining 36% are female. Out of the 25 respondents, 80% lived in central and over 64% was between 26-35 age bracket. 20% of the respondents were between 36-50 whereas the remainder was between 17-25.

|  |  |  |
| --- | --- | --- |
| **Variable** | **Percentage** | **frequency** |
| **Gender** |  |  |
| Male | 64% | 9 |
| Female | 36% | 16 |
| **Residence** |  |  |
| Central | 80% | 20 |
| West | 40% | 10 |
| North | 32% | 8 |
| East | 20% | 5 |
| **Age** |  |  |
| Below 18 | 0% | 0 |
| 18-25 | 16% | 4 |
| 26-35 | 64% | 16 |
| 36-50 | 20% | 5 |
| Above 50 | 0% | 0 |

Table 4‑1 Showing demographic information.

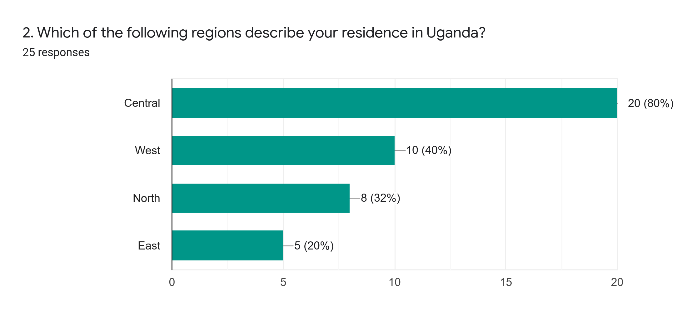
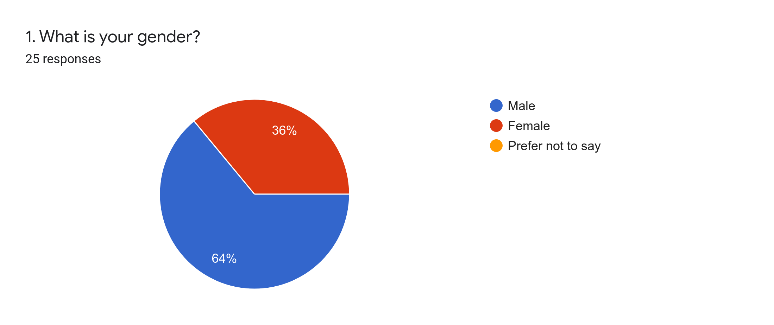


Figure 4‑1 Age demographics

Figure 4‑2 Residence Demographics

### End users.

For the end users, the survey was done with 45 respondents of which 62.2% were male and the rest female. 66.7% of the users lived in an urban setting whereas the rest lived in a semi-urban setting. 35.6% of them were between 18-25 years, 28.9% for those between 26-35 and 35-50 years whereas the rest where above 50 as shown below.

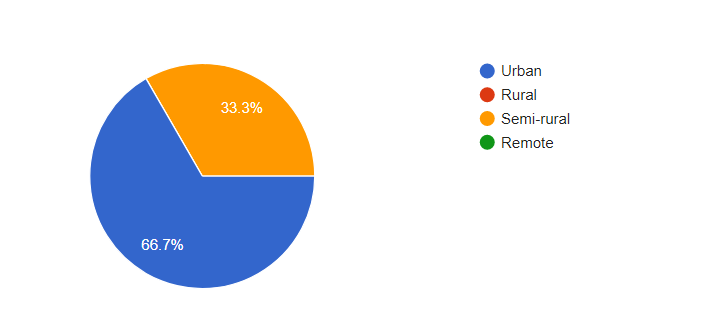
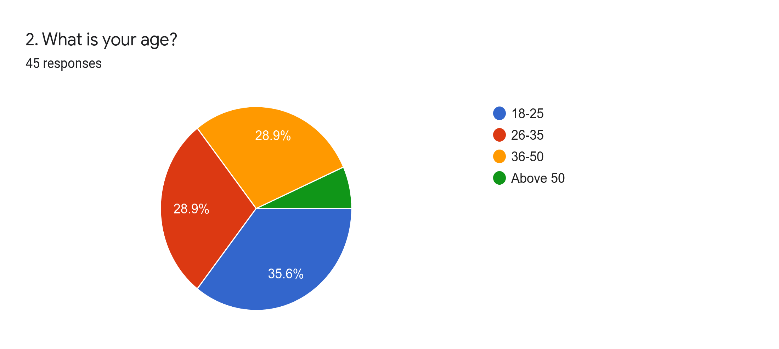
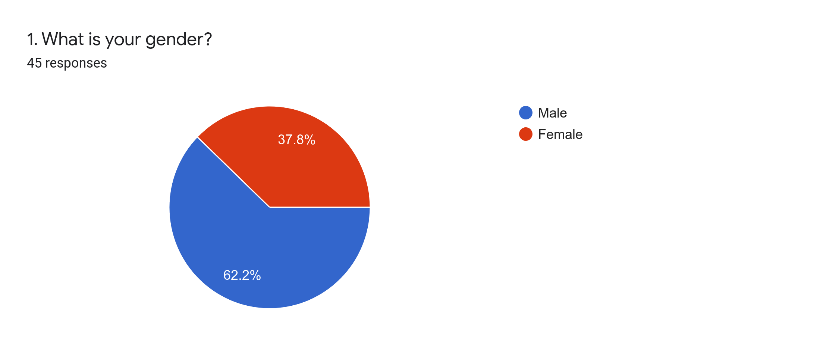


Figure 4‑3 Demographics for the end users

Insurers using automated systems

## Nature of Automated Underwriting systems used.

It is clear from the study that most insurers are using automated underwriting systems. The data shows that Rules-engine based systems are predominant. Of the 17 insurers with automated underwriting systems, 64.7% use rules-engine based systems whereas 23.5% of insurers have deployed a machine learning predictive model, only 11.8% outsource their systems.

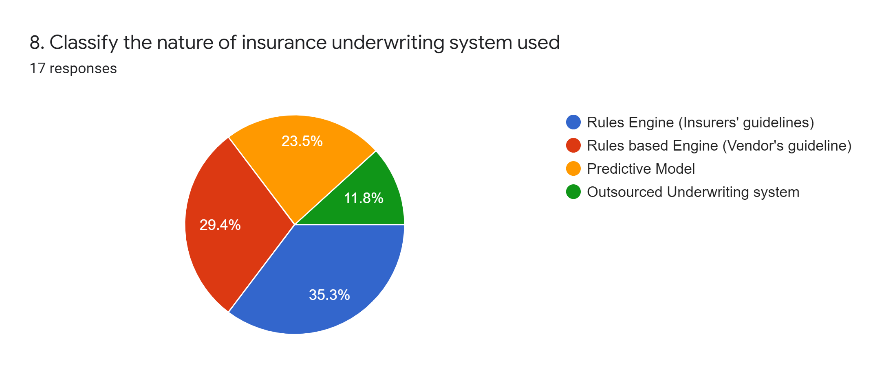


Figure 4‑4 Showing Nature of systems used

The rules-engine based are further divided into 2 categories; one with insurer’s guidelines and the other with vendor’s guidelines. Rules-engines based on insurer’s guidelines seem to be predominantly used over any other type of system. The chart in Figure 4‑4 summarizes the nature of systems used.

When choosing to implement automated underwriting life insurers have the choice of developing a home-grown system or purchasing one from a vendor. Only two of the systems covered in this study were developed by the insurer, while all others were vendor-based systems. In most cases, however, the vendor solutions are not off-the-shelf. Instead, they require significant customization. Insurers interviewed have had varying experiences working with vendors for customization, which will be discussed later in this report.

Another trend that became apparent throughout the interviews is that the automation of underwriting involves a transformation in the way an application is taken. While some companies still allow agents to submit applications in a traditional paper process and then enter the data into the system manually, all allowed and nearly half forced information communicated by the applicant to be submitted in an electronic format. To fulfill this requirement, participating life insurers utilize an online electronic application, a tele-interview, or both. The electronic and tele-applications are represented in roughly equal proportion in the study population. Not only are they often used together, in many cases, implementation of automated underwriting is accompanied by implementation of one or both of the electronic or tele-application processes. Although technically distinct from automated underwriting, some of the most spirited conversations about cultural acceptance were about changes to the application process.

## Applications of automated underwriting.

There are wide ranges of how much of each insurer’s business is handled by the automated underwriting system, how often the system is able to make or recommend underwriting decisions, what capabilities do the systems have? Below is a summary of the application of the systems used in underwriting.

|  |  |
| --- | --- |
| Does the system have the capability to | |
| Reduce underwriter’s time required to make decisions | 34.8% |
| Reach decisions without underwriter’s intervention | 16.2% |
| Recommend decisions for review | 20.9% |
| Reduce requirements ordered | 16.2% |
| Other | 11.9% |

Table 4‑2 Systems’ Abilities to either Reach or Recommend an Underwriting Decision

|  |  |  |  |
| --- | --- | --- | --- |
| How often does the system? | Average | St-dev | Range |
| Reach a final underwriting decision without underwriter review | 33.8% | 34% | 100% |
| Recommend an underwriting decision for an underwriter to review | 34.2% | 39% | 100% |
| Fail to reach or recommend an underwriting decision | 32% | 27% | 100% |

Table 4‑3 Actions taken by automated underwriting systems.

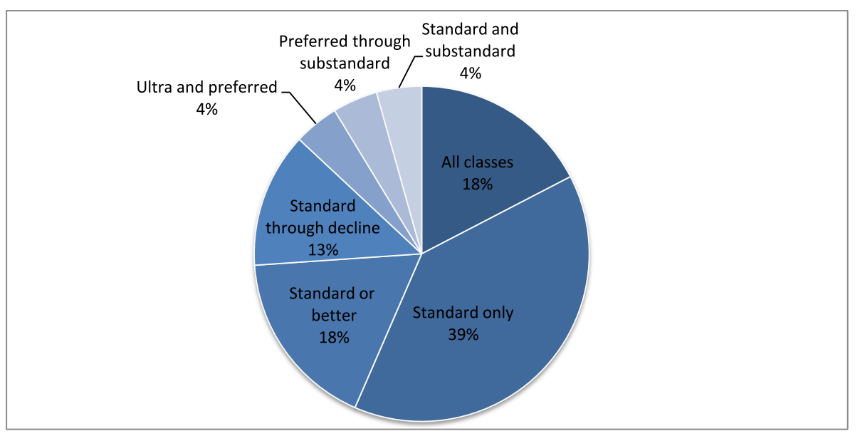


Figure 4‑5 Combinations of Risk Classes Available to Automated Systems

## Operational Efficiency – The ability of automated systems to improve the efficiency of the underwriting process

After discussing how the firm is using automated underwriting, the next topic explored was the impact on operational efficiency. The two topics of greatest interest were changes to underwriting cost and process time. Study participants were asked to either compare business underwritten with an automated system to the same type of business before implementation of automated underwriting or to similar business still underwritten through a traditional process. These discussions revealed the success levels for improving operational efficiency varied significantly among the participants. Further, the degree of success tends to vary based in part upon which of the three applications of automated underwriting the life insurer employs as shown in .

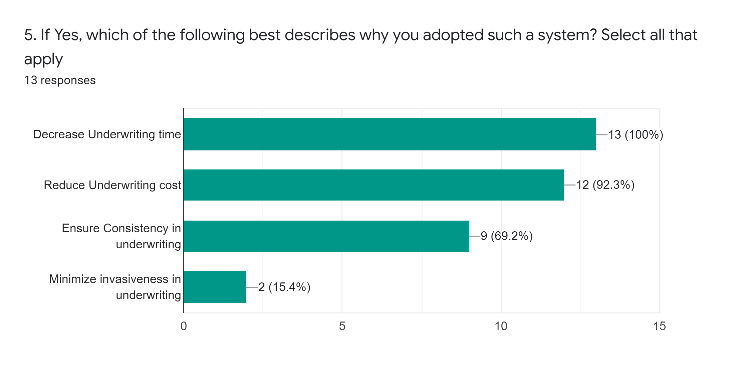


Figure 4‑6 uses of automated underwriting

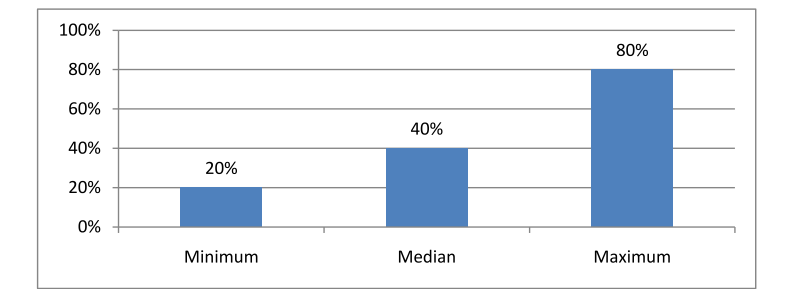


Figure 4‑7 Percentage Cost Savings from Automated Underwriting among Satisfied Insurers

The dominant savings achieved is via a reduction in the amount of underwriter time required during the underwriting process. For systems that make or recommend underwriting decisions, underwriters are asked to spend less time on simple cases. When automation raises flags for questionable information, the underwriter saves time by not reviewing the other pieces of information. In addition, several insurers cited a reduction in the time underwriters spend either providing updates to or negotiating with producers. Many insurers also utilize systems where agents can log in and check the status of a particular case. While a call to an underwriter inquiring about an application status may only last several minutes, this time easily accumulates as underwriters are covering multiple cases simultaneously. This time saved has produced meaningful savings. The insurers pleased with the cost saving performance came predominantly from those using automated underwriting for rapid issue or to flag outlying requirements. Potentially, because the underwriter’s time constitutes a larger fraction of underwriting costs on small cases than it does when more medical tests are necessary, the decrease in underwriter involvement is more significant to these companies. For larger cases, using automation in underwriting as a flag rather than a replacement for underwriters appears to offer the greatest return on investment.

# Summary, Conclusion and Recommendation

From the findings, it is evident that insurers who use automated underwriting use rules-based engines and those who had deployed predictive models had challenges with deployment. Data analytics is now the trend that is gaining significance among companies worldwide. In the life insurance domain, predictive modeling using learning algorithms can provide the notable difference in the way which business is done as compared to the traditional methods. Previously, risk assessment for life underwriting was conducted using complex actuarial formulas and usually was a very lengthy process. Now, with data analytical solutions, the work can be done faster and with better results. Therefore, it would enhance the business by allowing faster service to customer, thereby increasing satisfaction and loyalty. The research demonstrated the use of Machine learning in Insurance underwriting and the impact it has on future of life insurance.

Future work relates to the more in-depth analysis of the problem and new methods to deal with specific mechanisms. Customer segmentation is the division of the data set into groups with similar attributes can be implemented to segment the applicants into groups with similar characteristics based on the attributes present in the dataset. For example, similar employment history, insurance history, and medical history. Following the grouping of the applicants, predictive models can be implemented to contribute to a different data mining approach.

Dashboards can be extended depending on the availability of the data. For instance, financial dashboards can be built showing the premiums received and claims paid by the firm within a given period to ease profit and loss analysis. Another report can be of sales showing policy sales by different customers and time of the year, so that marketing strategies could be improved.

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