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Life Insurance for the Digital Age: An End-to-End View

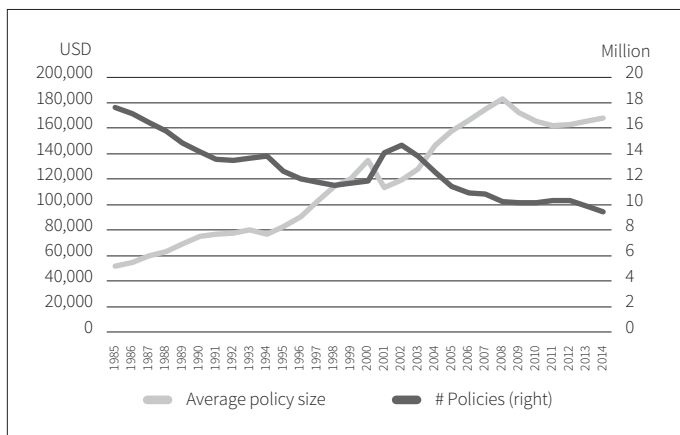
By Nitin Nayak and Stephen Abrokwah

According to a Swiss Re study, life insurance ownership has declined at a dramatic rate over the past 30 years and is currently at a 50-year low.¹ This situation is most pronounced among the middle market and millennial households. Declining sales partly explain the research estimates of the life insurance protection gap,^{2,3} which has been estimated to exceed USD 86 trillion globally and USD 20 trillion within the United States alone. The average household protection gap within the United States is now estimated to be just under USD 400 thousand.

Independent and captive agents constitute the majority of the existing distribution channels for life insurance products, and they have gradually migrated toward supporting mostly high net-worth individuals for larger face amount policies (See Figure 1). As a result, many in the mid-market segment are left to their own sources for both educating themselves and purchasing life insurance products.

With a greater availability of both internal and external data, along with advances in predictive models, an increase in

Figure 1
Individual Life Insurance Sales⁴



Source: Swiss Re Economic Research and Consulting.

competitive pressures, and a shift in demographics toward millennial and Gen X generations, it is now an opportune time for primary insurers to reassess the traditional approaches for addressing the protection gap. The industry has started examining this issue from multiple viewpoints along the customer journey. Recommendations include educating customers about the value and affordability of life insurance, reducing the friction and waiting times in the buying process, and improving the quality and speed of assessing/pricing customer's mortality risk. As a result, existing actuarial methods are being supplemented with several nontraditional data sources and modelling techniques, which are currently in various stages of deployment. This article provides an overview of various innovative solutions supporting an end-to-end underwriting process for life insurance products.

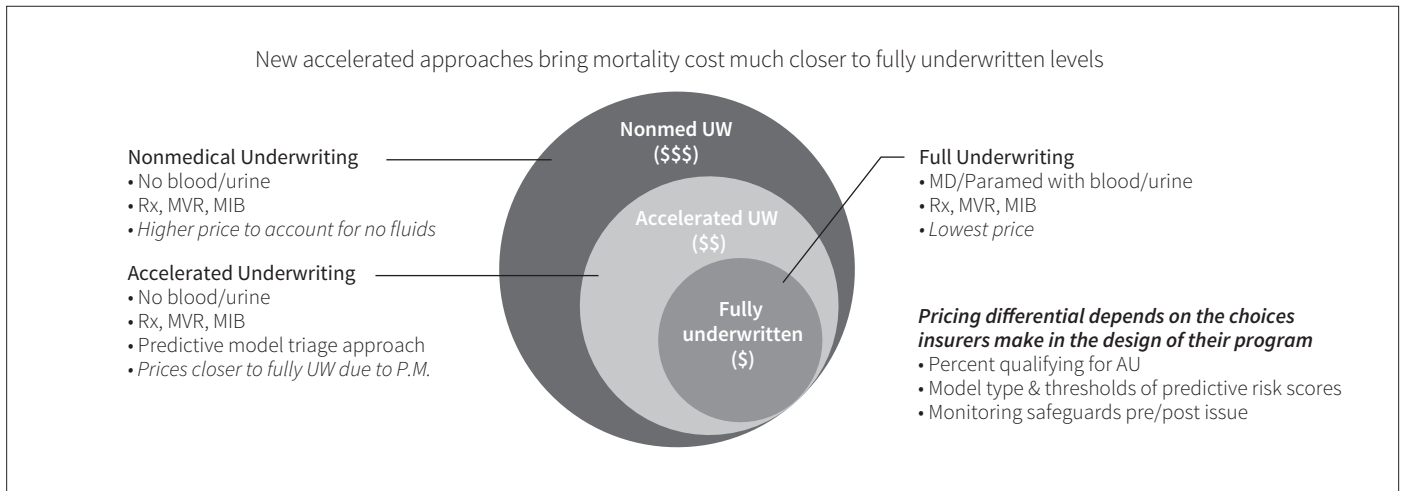
EVOLUTION OF THE TRADITIONAL LIFE INSURANCE BUYING PROCESS

Life insurance plays an important role in protecting households and families from the dire financial impact of uncertain mortality. Over the years, actuaries have developed robust estimates of life expectancy by using mortality tables to predict aggregate insured population mortality as well as dependable underwriting techniques to assess the relative risk of an individual. Though these techniques have been widely accepted within the insurance industry for many years, the traditional life insurance underwriting process is time-consuming, invasive and costly. Typically, a life insurer spends about a month and several hundred dollars underwriting each proposed insured, with underwriting costs ultimately passed on to policyholders through increased premium rates.³

Over the years, the life insurance industry has been gradually streamlining the underwriting and customer sales processes to make them less invasive and to provide a more timely response. Some early enhancements included simplified issue products with easier application requirements and nonmedical underwriting for smaller face amounts, and refinements of underwriting guidelines based on protective value studies.

The increased availability of individual-level data, new sources of nontraditional information, and advances in machine learning techniques have created an opportunity for life insurers to embrace innovations in various areas along the insurance value chain. In the context of underwriting, this innovative revolution utilizes predictive analytics, underwriting automation and business intelligence to underwrite with faster turnaround times, reduced costs and fewer invasive medical requirements. This win-win situation for insurers and prospective policyholders should help insurance companies to increase sales, improve their bottom line and provide a better customer experience to proposed insureds. This transformation, however, is not without its challenges, especially when it comes to the mortality

Figure 2
Mortality Cost Implications of Various Underwriting Approaches



implications. Figure 2 shows the relative increase/decrease of mortality costs for various approaches being explored within the industry. In comparison to a full underwriting process with its detailed and time-intensive procedures, the faster nonmedical (no paramedical exam, blood or urine test, or attending physician statement) underwriting process increases the expected mortality cost. Alternatively, transitioning from nonmedical underwriting to fluid-less underwriting, supplemented with predictive analytics, can bring expected mortality to levels closer to that of a fully underwritten process.⁵

LIFE INSURANCE FOR THE MIDDLE MARKET AND MILLENNIAL GENERATION CONSUMERS

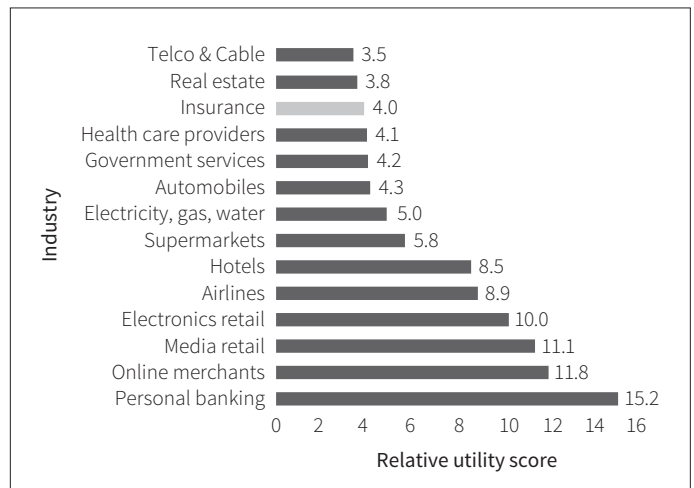
Life insurers can learn much from other industries, including online retail and personal banking, to improve the customer satisfaction of their consumers. This is especially true for the millennial generation who would likely prefer to purchase life insurance products online. Figure 3 shows the results of a consumer survey regarding satisfaction with online experiences across various industries. Clearly, the insurance industry lags behind when it comes to delivering a satisfactory online consumer experience.

To increase customer satisfaction, especially for the millennial generation, we suggest primary insurers offering life insurance products consider the following consumer expectations:

- The ability for the consumer to get a quick tutorial on life insurance products, with a concise explanation of their benefits
- An individualized needs analysis for each consumer, along with a recommendation for various life insurance products (term versus permanent), and face amounts based on their individual life situation.

- A simple application process requiring fewer questions, with as many fields in the application prefilled with user-specific information as appropriate
- A quote delivered in real time describing the policy coverage and associated premium and payment options, similar to the experience of purchasing automobile insurance online
- A set of relevant quote alternatives, each outlining policy coverages and associated premiums for the user to compare to the face amount originally requested by user
- A view of life insurance and related products (e.g., riders and term periods purchased by the consumer's peers in order to assist with decision making)

Figure 3
Consumer Satisfaction with Online Experience by Industry⁶



The next section presents a view of the end-to-end process for purchasing life insurance products from the perspective of a life insurer.

OVERVIEW OF INNOVATIONS FOR ACCELERATED UNDERWRITING IN LIFE INSURANCE

This process starts with the customer being presented an online insurance application in a shorter form and with prefilled responses (where possible) to make it more likely to be completed. At the end of the process, the customer will be offered multiple affordable and suitable quotes within minutes based on an individualized needs analysis. Figure 4 provides descriptions of these steps.

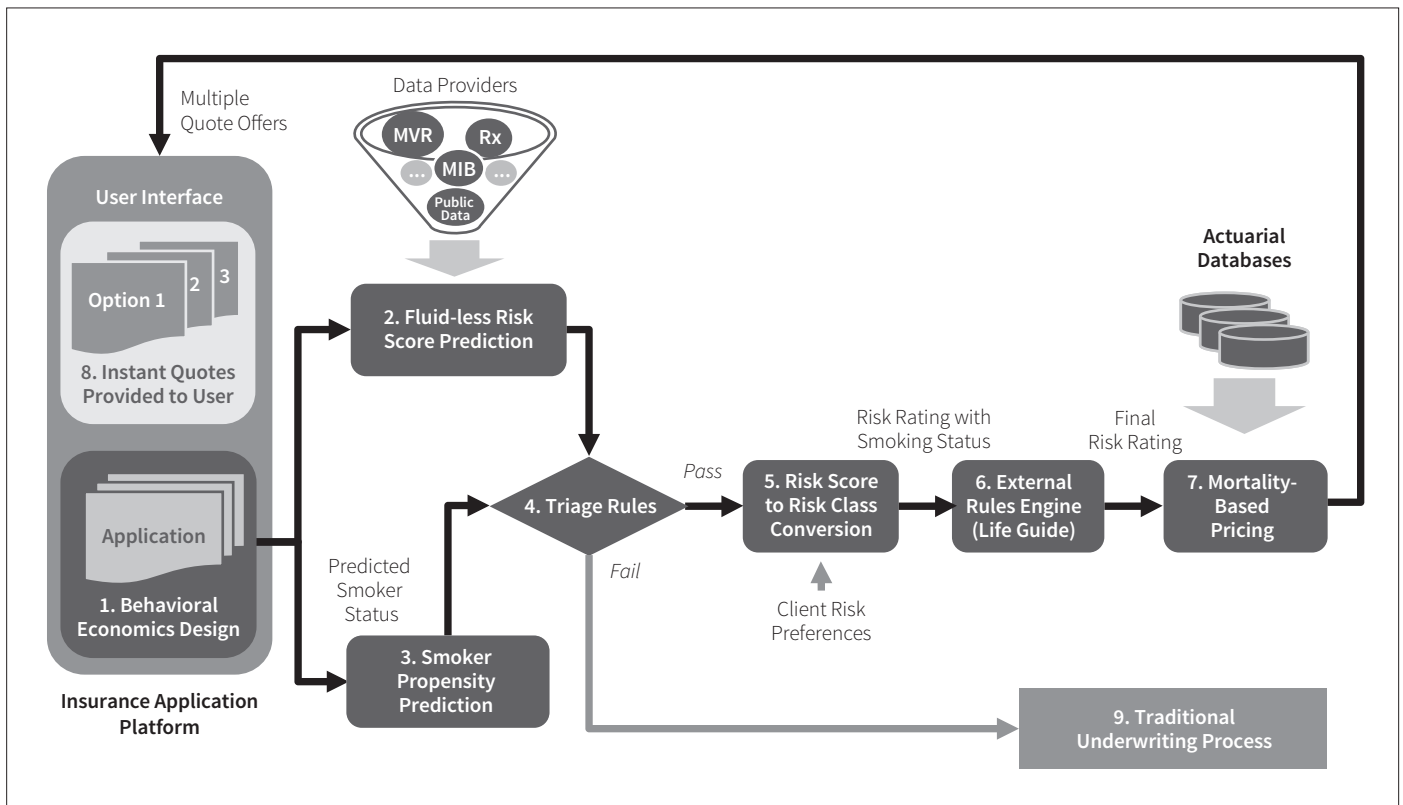
Step 1. User Interaction

Most millennials are very comfortable using mobile technology for their online interactions, both in the social world of friends as well as the commercial world of transactions. Additionally, they expect to make their own decisions (self-service) and prefer only occasional hand-holding to complete any transaction. So although digital, mobile and online platforms are not currently the dominant channels for most insurers to interact with potential customers, we expect that within the next few years, many

life insurers will leverage these platforms as key distribution channels. For example, many life insurance carriers like Massachusetts Mutual Life Insurance Company (Haven Life) and AAA Life Insurance Company have begun offering sales via online and other digital platforms.

Another challenge faced by life insurers is the application format, which today contains upwards of 60 questions covering a variety of individual details along with invasive medical tests and a long wait time of approximately 45 to 60 days.⁷ For the millennial and most middle-market consumers, the large number of questions and the time commitment required can be a deal-breaker. From an insurer’s point of view, this long-form application is necessary to properly assess the applicant’s mortality risk and to prevent anti-selection. However, not all questions in the application questionnaire have the same predictive power. Machine learning techniques can identify the most important features for predicting mortality risk so the least useful features can be removed to simplify the questionnaire. Some insurers are exploring the extent to which the application can be prefilled with data from other internal and external sources. This should make it easier for the consumer who can now focus mostly on correcting any incorrect prefilled information. Additionally, many insurers are

Figure 4
End-to-End View of Accelerated Underwriting Process



beginning to utilize behavioral economics theory in pilot trials to test how rearranging or reframing application questions can improve the veracity of the applicant’s responses.^{8,9}

Step 2. Risk Score Prediction

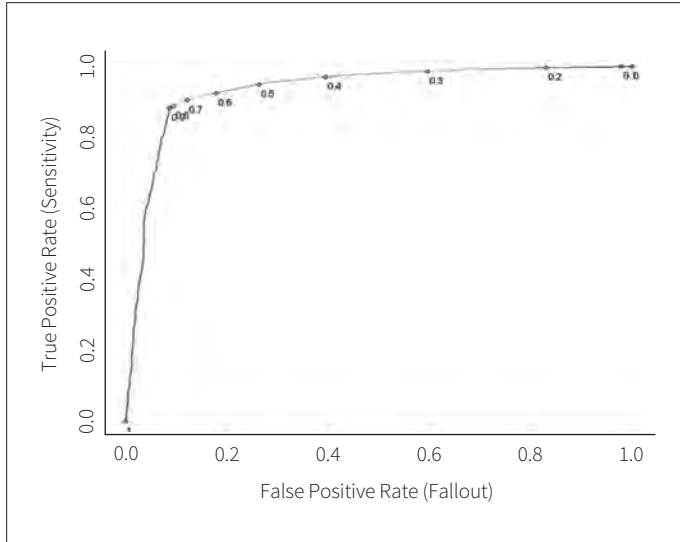
Correctly assessing an individual’s mortality risk is critical for the life insurance underwriting process. Traditionally, this assessment has depended on an underwriter reviewing the individual’s answers to application questions including family and medical history and the individual’s propensity for risk-seeking behavior expressed through hazardous avocations. Additionally, third-party vendors may have provided a proposed insured’s prescription profile (Rx), motor vehicle records (MVR) and medical information on major health issues (MIB) that can affect mortality risk. Many life products also require services

of paramedical staff to collect fluids and conduct a basic medical exam to assess blood pressure, BMI and pulse. Although this approach has become a standard operating procedure for underwriting many life insurance products, it suffers from both high costs and lengthy time delays, resulting in lower customer satisfaction and higher proposed insured dropout rates. Many life insurers have therefore from our observation started moving toward creating a more customer-centric experience that removes medical exams and fluid-testing for a majority of the applicants. To this end, the use of nontraditional data sources and predictive models are helping better assess an applicant’s mortality risk in new ways. Table 1 lists some existing and non-traditional data sources being leveraged for predicting mortality risk in addition to applicant-provided information.

Table 1
Sample Data Elements for Building Mortality Risk-Related Predictive Models

Data Element	Description and Examples	Usage Within Life Underwriting
Third-Party Data	<ul style="list-style-type: none"> • MIB for medical information • Rx for prescription history • MVR for motor vehicle record 	To validate proposed insured’s prior medical and insurance purchase history, prescription profile and propensity to take risks (e.g., through review of proposed insured’s driving record)
Public Data	<ul style="list-style-type: none"> • Properties, professional licenses, criminal history 	To validate applicant-provided data as well as to fill in missing information
Financial	<ul style="list-style-type: none"> • Income and employment history • Short-term and long-term debt (mortgage) • Bankruptcies, liens 	Used as one of the predictors to predict mortality risk, especially for low-risk individuals
Credit History	<ul style="list-style-type: none"> • Credit score 	Used as one of the predictors to predict mortality risk, especially for low-risk individuals
Digital Imaging	<ul style="list-style-type: none"> • Facial image analysis 	To assess individual’s age group, BMI, and smoking status
Social Data	<ul style="list-style-type: none"> • Publicly available social media such as Facebook, LinkedIn and Snapchat 	To verify identity, hobbies, smoker status, and use of alcohol or drugs, although the hit-rate may be low
Population-level Open Data	<ul style="list-style-type: none"> • Zip code and state-level published data on education levels, median income, disease, risky behavior etc., from sources such as U.S. Census, U.S. Centers for Disease Control • County/state tobacco taxes and regulations 	Although coarse in granularity, the data can still be useful to fill in missing data on individuals. The tobacco-related data can be used for smoker propensity prediction
Medical	<ul style="list-style-type: none"> • Access to electronic medical records 	To assess current and future risk related to health and mortality
Health and Wellness	<ul style="list-style-type: none"> • Vital statistics, heart rate, physical activity data collected from wearables and internet-enabled devices • Food preferences, psychological and emotional health from wellness websites and programs 	To assess current and future risk related to health and mortality

Figure 5
Prediction Performance—Comparing True Positive and False Positive Rates



Note: Steep slope of ROC curve indicates model predicts more true-positives with very few false-positives at threshold = 0.8

Step 3. Smoker Propensity Prediction

After age and gender, tobacco usage is the most important determinant of mortality risk and hence of life insurance policy premium. According to the Centers for Disease Control (CDC), overall mortality among both male and female smokers in the United States is about three times higher than that among similar people who never smoked.¹⁰

In the United States we see actuarial pricing tables routinely load up premium rates to 200 percent, and in some cases well in excess of 200 percent for tobacco users, especially smokers.

Traditionally, presence of cotinine in the blood sample during lab testing has been used to identify tobacco users. However, in the absence of any form of fluid testing within an accelerated underwriting process, one needs alternative approaches to separate tobacco users from nonusers. In today's data-driven world, the use of predictive analytics for identifying smokers and nonsmokers is being actively explored by several insurers. From our experience, the initial results using data-driven approaches look promising, and as shown in Figure 5, the steep ROC curve¹¹ suggests that the model can correctly predict many true-positives while making few mistakes (false-positives). Since the cost of misclassifying smokers as nonsmokers is much higher than misclassifying nonsmokers as smokers (due to increased mortality cost, and potential lost premiums in the former, and applicant aggravation in the latter), the performance metric that is more relevant is precision,¹² that is, how many predicted true-positives are actual true-positives.

The precision requirement, however, is best decided based on calculating the financial impact of misclassification error, by conducting a cost benefit analysis.

Step 4. Rule-Driven Application Triage

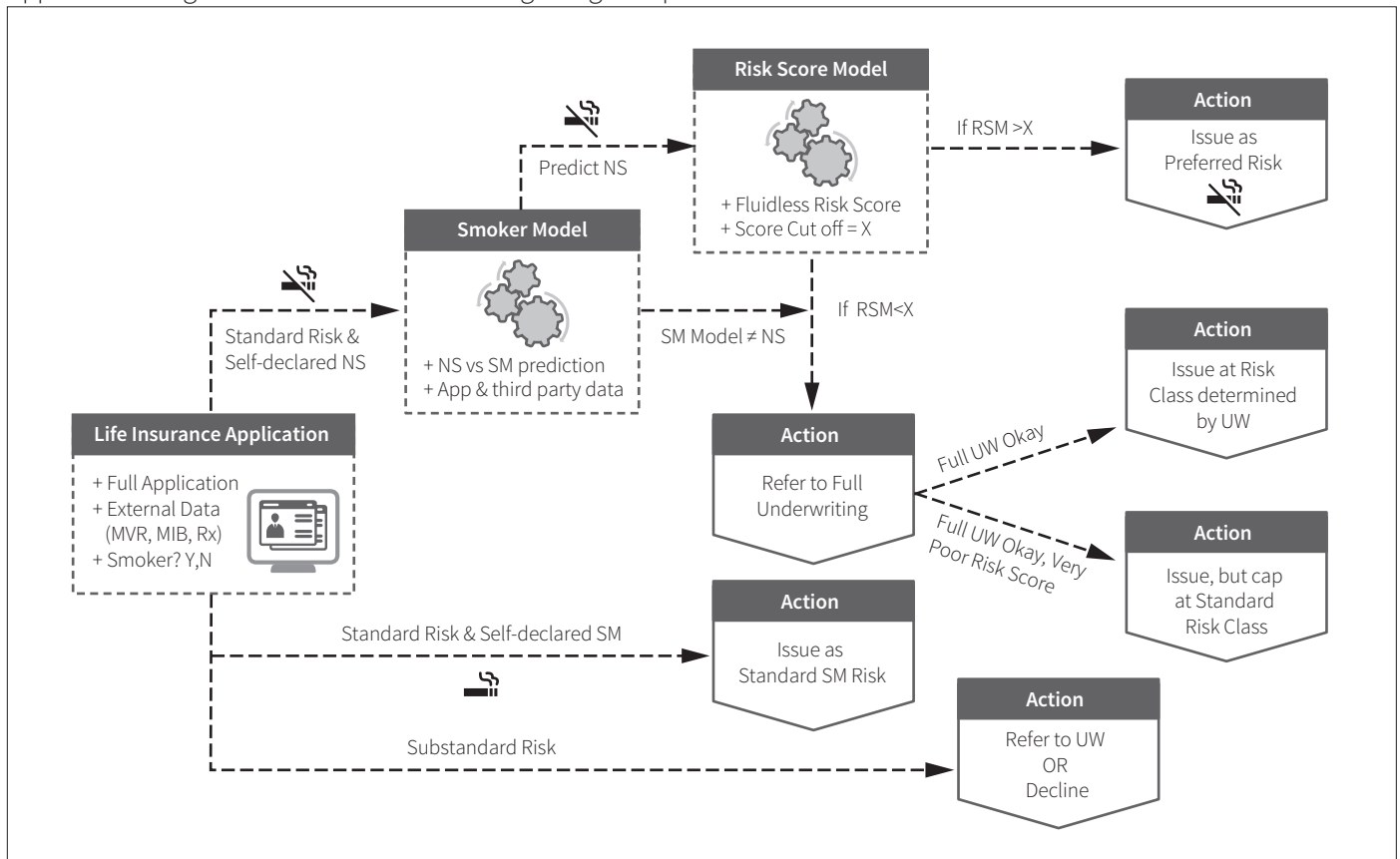
The vision of having an end-to-end, fully automated, data-driven approach to underwriting is appealing, but many companies would prefer to evolve in a more nuanced and deliberate way. Many are exploring alternative business processes whereby the output of a predictive model feeds into a triage step. Predicted low-risk applicants can then proceed ahead through the fast-track process, while the predicted high-risk applicants are asked to proceed via the traditional process. Subject to regulatory guidance, there could be multiple types of triage scenarios for fully underwritten products. Figure 6 shows an example of a multistep triage approach designed to direct applicants to the next step in the end-to-end accelerated underwriting, based on their risk rating and their predicted smoker/nonsmoker status. The figure illustrates the sequence of applications and third-party databases used to triage applications in preparation for assigning them to a risk class.

Step 5. Risk Classification Using Risk Score Thresholds

There are two approaches to predicting the mortality risk of a proposed insured applicant by using a risk score: either use the score to predict the risk class that would have been assigned by an underwriter, or use the score to predict the expected mortality, which can then be converted into an appropriate risk class.



Figure 6
Application Triage for Accelerated Underwriting Using Multiple Predictive Models



Generally, the first approach is easier to sell to the underwriting community; however, the second approach is a more objective way of assessing a proposed insured's mortality risk.

We note that when validating the predicted risk class against the historical underwriter-derived risk class for an application, the predicted risk class could be different from the underwriter's decision. The movement of applicants across risk classes is most common for those applicants whose scores are near the borderline between two classes. However, the objective measure should be the relative actuals-to-expected (A/E) mortality ratios for various risk classes, where the better underwriting risk is represented by a lower A/E ratio. During deployment of a risk scoring solution, the choice of associating risk classes with risk score intervals is very much left to the insurance company but can be selected based on comparable A/E ratios for the risk class and corresponding risk score interval.

Step 6. External Rules Engine

The data-driven predictive analytics approaches address the risk score prediction and tobacco usage prediction in steps 2 and 3 respectively. Before the introduction of new predictive analytics

techniques, the most common approach to underwriting decisions had been the use of experience-based rules that resulted from several proprietary and industry-sponsored research studies. These rules generally apply an extra loading for mortality-increasing risk factors within the preferred criteria. Examples of such risk factors include family history of significant illnesses of either parent, participation in hazardous avocations, just to mention a few. The rules engine sums up the total risk factor loading for a proposed insured, which is then compared against a table to assign a risk class. From this perspective, the external rules engine can complement the predictive models with experience-based rules to further refine the risk class assigned to an applicant. So it is not surprising that many insurers require that decision rules for underwriting be included within their end-to-end accelerated underwriting process.

Step 7. Mortality-Risk-Based Pricing Algorithms for Quote Generation

Although the details of mortality-based pricing models are outside the scope of this article, many insurers use pricing tables based on age, gender, risk-class and tobacco usage of an individual to compute the premium for life insurance policies of

specific face amount and level term periods (for term products). The process flow as described in Figure 4 essentially provides these variables required by the mortality-based pricing algorithm to support a real-time quote. A useful feature can be to compute prices for multiple combinations of face amounts and term periods, based on historical choices made by other users, with situations similar to the applicant. These multiple pricing options can then be presented to the customer as described in Step 8, to help make a life insurance buying decision that best suits his or her situation.

Step 8. Real-Time Customer Response

In responding to a customer's request for a life insurance policy, the goal should be more than just fast response time. In addition to providing a quote in real-time for the face amount requested, it would also be helpful to offer assistance to the customer to make a buying-decision. If viewed from this perspective, the process could also include:

- Providing various alternative solutions that cover not just the requested face amount and term period but also other face amounts and term period combinations, in case the requested coverage is beyond the customer's financial reach.
- Providing an alternative life insurance product to the customer, should the customer not qualify for the original coverage requested.
- Illustrating how each offered policy provides coverage for various adverse life events that the individual could face besides the ultimate death benefit, in the form of life insurance riders relevant to their situation. This should help the customer to better understand the complete benefits offered and thus optimize the potential to complete the sale.



- Providing an overview of life insurance products and coverage that “people like me” have purchased, with a corresponding distribution of such product purchases by age, gender and location. This again should help increase the customer's confidence about their buying decision.

Step 9. Traditional Underwriting of Selected Applicants

Assuming the issuing carrier meets all regulatory requirements in the relevant jurisdictions, steps 1 through 8 provide an overview of an accelerated underwriting process that could work for a significant portion of applicants who pass the required database checks as well as various cutoff thresholds set for the predictive models, depending on the pricing goals of the company. However, there will be situations that are difficult to resolve through the fast-track process, such as when an applicant has poor scores from the risk score prediction model or the smoker prediction model warrants further investigation. These situations should result in the applications getting redirected out of the triage process (as shown in Step 4), to go through the traditional underwriting process, wherein an underwriter can review and assign the appropriate risk class to the applicant.

... continuous improvements in the prediction accuracy of new analytics approaches/models should allow insurers to offer coverage using accelerated underwriting programs for higher face amounts and at premium rates closer to fully underwritten products.

CONCLUSION

One can argue that underwriting has always been data-driven with application details, lab and examination results, and vendor data feeding into the underwriting process implemented through a set of rules and supported by an underwriter's judgment. In that sense, advances in underwriting are not as much about being data-driven as they are about leveraging advanced analytics or machine learning techniques,¹³ and nontraditional data sources to assist with mortality prediction. The promise of advanced machine learning models is to be able to predict tobacco usage and mortality risk score for all proposed insureds at levels of accuracy rivaling human underwriters.

Currently, insurers offering instant issue life insurance products with no human in the loop are limited to simplified-issue products. To address veracity concerns posed by less-than-truthful applicants, these products mostly mitigate risk by limiting coverage to lower face amounts and at premium rates higher than traditional, fully underwritten products. We believe that continuous improvements in the prediction accuracy of new analytics approaches/models should allow insurers to offer coverage using accelerated underwriting programs for higher face amounts and at premium rates closer to fully underwritten products. In our view, prediction accuracy of current state of the art models is acceptable for proposed insureds who have inherently low to medium mortality risk. Nonetheless, this group is a significant part of the applicant population and so insurers can still realize significant benefits by implementing current state of the art models. For the remaining medium- to high-risk individuals who traditionally have been processed by human underwriters, a simplified issue product or a rated product determined by an underwriter should address the current prediction accuracy gap.

As successful as the initial foray into this pattern-based predictive analytics approach has been, it is still evolving. However, we have no doubt it will find its place in life insurance underwriting, especially as these analytics approaches are refined in accordance with developing regulatory guidance. ■



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ENDNOTES

- 1 *The US Mortality Protection Gap—An update*. Milka Kirova, Swiss Re Economic Research & Consulting, August 2015, http://institute.swissre.com/research/overview/insurance_monitoring/the_US_mortality_protection_gap_an_update.html.
- 2 Measured as the difference between the amount of coverage held by individuals or households and the optimal amount cover needed in the event of the demise of the breadwinner of a household.
- 3 *Mortality Protection Gap in the US*, Swiss Re Economic Research & Consulting, 2012, http://www.swissre.com/library/publication-sigma/The_mortality_protection_gap_in_the_US.html.
- 4 Individual life insurance sales drop and distribution of life products has shifted from mid-market to high net-worth individuals.
- 5 *Simplified Issue and Accelerated Underwriting*. The Society of Actuaries and the American Academy of Actuaries, 2016, https://www.actuary.org/files/publications/SL_AUW_LATFPresentation_12.8.2016.pdf.
- 6 Consumer survey regarding satisfaction with online experiences across various industries constructed from a Boston Consulting Group study
- 7 *Predictive Modeling for Life Insurance*. Deloitte Consulting LLP, April 2010, <https://www.soa.org/files/pdf/research-pred-mod-life-batty.pdf>.
- 8 Behavioral Economics—Simple changes creates “more moments” like this, Swiss Re case study (Swiss Re internal data).
- 9 *How Using Behavioral Economics Can Improve Underwriting Results—Risk Insights*. Marchy Updike, GenRe, January 2017, <http://www.genre.com/knowledge/publications/ri17-1-en.html>.
- 10 *The Health Consequences of Smoking—50 Years of Progress. A Report of the Surgeon General*, U.S. Department of Health and Human Services. Atlanta: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Chronic Disease Prevention and Health Promotion, Office on Smoking and Health, 2014.
- 11 The graph in Figure 5 is called a receiver operating characteristic curve (ROC curve). It is a plot of the true-positive rate against the false-positive rate and shows the tradeoff between sensitivity and specificity for different possible cutoff points. The area under the ROC curve is a measure of predictive model accuracy. The closer the curve is to the top-left corner, the more accurate the predictive model, while the closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the predictive model.
- 12 Precision (also called positive predictive value) is the fraction of predicted positive instances that are correct. A perfect precision score of 1.0 means that every predicted positive instance is correct prediction.
- 13 In this regard, enabling all insurers to capture application data in digital format should be high on the priority list of both life insurers and industry consultants.