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# The Impact on Relative Mortality and Prevalence from Triage in an Accelerated Underwriting Program

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**A**ccelerated underwriting programs continue to evolve at a rapid pace. Triage systems have become a key element in many of the newer accelerated underwriting programs in the market. Depending on the criteria used at the triage point, these programs can have residual effects on class prevalence and mortality which in turn affect the profitability of these programs. In this article we will explore some potential impacts on mortality and prevalence within these programs.

## HISTORY OF ACCELERATED UNDERWRITING

In the individual life insurance space, accelerated underwriting (AUW) is the newest iteration of underwriting. In these programs instead of collecting blood and taking the physical measurements of the applicant, underwriting relies on self-reported measurements along with information from various databases and scoring tools.

### AUW 1.0

In early accelerated underwriting programs, companies simply changed their age and amount requirements. For certain ages and face amounts, para-medical exams and fluid testing were replaced with checks on prescription drug (Rx) and motor vehicle records (MVR) databases. The mortality impact of removing fluids was assessed as a load to the company's fully underwritten mortality assumption which was partially offset by a discount associated with the protective value of the new underwriting tools and expense savings. In addition, because these changes meant that the underwriting decision would be based on self-reported information rather than tested information (e.g., build and smoker status), loads were introduced to account for asymmetry of information and additional adverse selection.

These early programs often passed on the net increase in expected mortality to the end consumer. Also the first adopters

of these programs usually did not allow for preferred risk classes. Thus these programs were not priced competitively and were prone to additional adverse selection. Few, if any, of these programs achieved their sales targets, and the mortality experience often performed poorly.

### AUW 2.0

In order to make these products more attractive in the market and with the intent of attracting better risks, companies started to introduce various changes. The following chart outlines the general evolution of these products over time.

Chart 1  
Progression of AUW over Time

Industry-wide	2010	2014	Today
Programs	A few programs; mostly simplified issue (SI)	A handful of products; a mix of SI and accelerated	Many programs of varying designs and target markets
Underwriting tools	MIB, MVR, Rx	MIB, MVR, Rx, other vendor tools, first-generation predictive models, interviews, reflexive questions	MIB, MVR, Rx, credit based scores, more sophisticated predictive models, interviews, reflexive questions, triage
Rules engines	Few	Half	Most
Non-smoker risk classes	One	2 or more	Same as fully-underwritten
Pricing	Table 4-8	10-15 percent loads	Fully-underwritten premiums
Maximum face amounts	\$100,000	\$250,000	\$500,000 or higher

The product parameters and underwriting tools in accelerated underwriting programs continue to evolve. This article will focus on a few aspects related to the use of underwriting triage to select better risks and/or to introduce a sentinel effect.

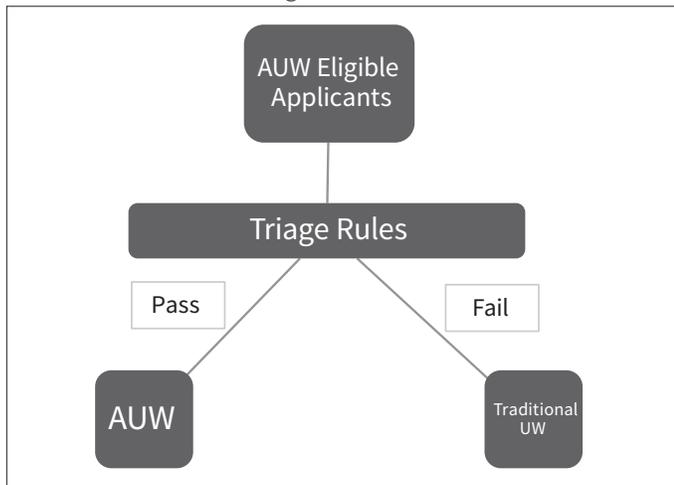
## TRIAGE

Triage in this context is the introduction of decision nodes in the underwriting process where the applicant is evaluated using a subset of the available information that provides predictive value. A major benefit of triage is the ability to restrict the availability of accelerated underwriting to those applicants exhibiting better risks or where there is a higher degree of confidence of



assigning an appropriate risk class. A human underwriter typically steps in for applicants with negative indicators, allowing the company to strike a balance between the expense savings of removing fluid underwriting and the extra cost of mortality due to the loss of fluid underwriting. An illustration of a simple triage system is presented in Graph 1.

Graph 1  
Basic Illustration of Triage



In this simple triage example, thresholds are set based on certain database checks and responses to the application questions. If the applicant meets these thresholds then the application proceeds to accelerated underwriting. If not, the applicant is required to undergo more traditional underwriting.

Examples of criteria used in triage models include the use of credit based risk scores or the use of prescription drug database

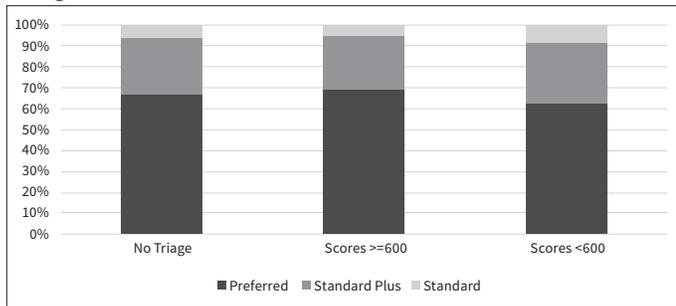
rules or scores, both of which have been shown to segment mortality.<sup>1 2</sup> As such, the use of triage creates a quasi-preferred class structure. This segmentation can impact both the risk class prevalence and relative mortality on each side of the triage, the degree of which varies with the level of correlation between the triage model's criteria and the company's preferred underwriting rules. On this spectrum of correlation, two extremes exist:

1. The triage model is uncorrelated with the preferred class underwriting rules.
2. The triage model and the preferred rules are highly correlated.

**Extreme 1: The triage model is uncorrelated with preferred class underwriting**

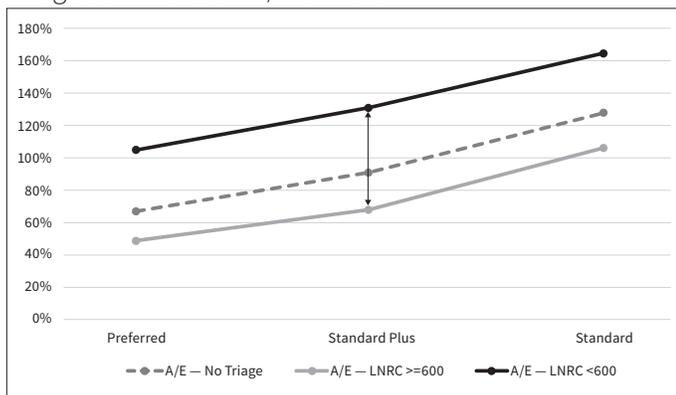
Under the first scenario where the triage model's selection criteria are uncorrelated with the preferred class underwriting rules, but the triage model is predictive of mortality, the pricing mortality assumption would require a path-dependent adjustment: one triage path would have better mortality and the mortality of the lives that are triaged to the other path would be higher. However, because this triage model's criteria are uncorrelated with preferred underwriting rules, each path should have roughly the same preferred composition.<sup>3</sup> In other words, if a triage model's selection criteria are uncorrelated with preferred underwriting rules, the model can shift mortality relative to full underwriting without affecting preferred class prevalence. Using only a credit based risk score cut off for the triage decision along with using only health information for the preferred class rules is an example of this extreme. This relationship can be seen in Graph 2, which displays class distribution shifts using Lexis Nexis Risk Classifier (LNRC), a credit based risk score, as the triage model:

Graph 2  
Triage at LNRC 600—Distribution Shifts



In this example, a fully underwritten sample population of about 500,000 lives were triaged at an LNRC score of 600. Note that the risk class distribution at and above a score of 600 is extremely similar to the distribution below 600. Scores below 600 are slightly biased toward standard traditional risk classes, but this bias is slight. For this population, LNRC score is a weak predictor of underwriting risk classes. Despite this, it is strongly predictive of mortality within risk classes. See Graph 3, which displays how an effective triage model with low correlation to preferred criteria can segment mortality within each risk class.<sup>4</sup>

Graph 3  
Triage at LNRC 600—A/E on 2015 VBT



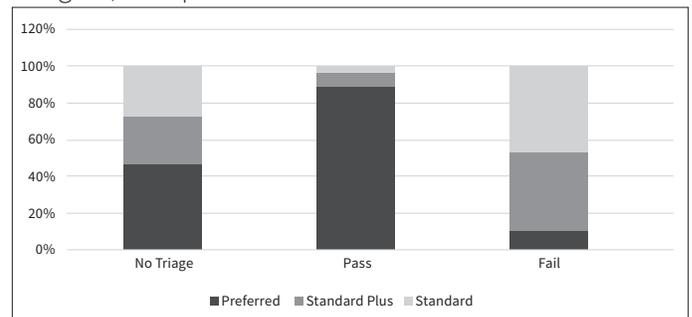
In Graph 3, A/Es relative to the 2015 VBT from the same population of about 500,000 are displayed both above and below the triage threshold. Note that the A/E vector for scores 600+ forms a nearly perfect parallel shift below the original population (labelled “No Triage”), and the vector for scores below 600 are a nearly perfect parallel shift above the original population. For this population, LNRC doesn’t just segment mortality within each class, it does so nearly identically between classes. Large mortality shifts are present on each side of the triage, but distribution shifts are immaterial. Keep in mind, though, that this

result is due to the relationship between LNRC and the specific preferred criteria used to segment the test population.<sup>5</sup>

**Extreme 2: The triage model and the preferred rules are highly correlated**

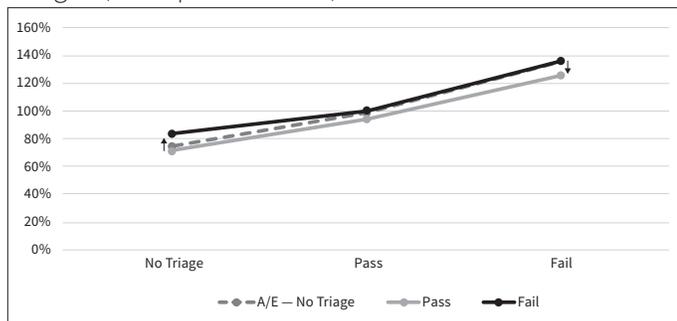
Some life insurance companies’ proprietary models segment mortality and classify risks similarly to their traditional underwriting. This is often by design, as sometimes companies calibrate their triage model criteria to mimic their traditional underwriting criteria. If successfully done, this would lead to a triage model that is highly correlated with traditional underwriting. This means minimal to no path-dependent mortality discounts or loads would need to be considered relative to fully underwritten assumptions, as risk selection between this model’s criteria and preferred underwriting are by definition very similar. Distribution shifts, however, should be considered. The point of a triage model is to separate good risks from bad; if a triage model’s criteria are highly correlated with preferred underwriting, it will categorize traditional preferred risks as “good risks,” meaning a disproportionate number of preferred risks will be sent down the accelerate underwriting path. As a residual effect, a disproportionate number of standard risks will be sent down the traditional underwriting path. This relationship can be seen in Graph 4, which displays class distribution shifts using a sample triage model, calibrated to mimic traditional preferred criteria:

Graph 4  
Triage w/ Sample Model—Distribution Shifts



By design, distribution shifts from this model are much more material than what was illustrated using LNRC. And assuming this model is predictive of mortality, the population in each class on the “fail” side of the population will have higher mortality than the “pass” side. However, most of the segmentation from this model is explained by its ability to separate preferred from standard risks, as a traditional underwriter would classify them. Therefore loads and discounts calculated to reflect fully underwritten class differentiation would largely apply here, with minimal adjustment needed. Graph 5 illustrates A/Es on 2015 VBT resulting from the sample model.

Graph 5  
Triage w/ Sample Model—A/E on 2015 VBT



Note that the largest shifts from the “No Triage” vector come from the exceptional cases—preferred risks who fail the model and standard risks who pass the model. With few exceptions (which make up a small distribution), A/Es segmented by this triage model are virtually the same as the A/Es of the original population. For this highly correlated extreme, large distribution shifts are present on each side of the triage, but shifts in mortality are small.

These two extremes above are bookends, but uncommon in reality. Most triage programs seem to fall between these bookends. Typically, material mortality and prevalence shifts should be expected, and each should be priced for, as each can independently affect a program’s profitability. This is important to note, as the effects of mortality shifts are obvious, whereas the effects of distribution shifts can tend to be overlooked.

### THE POTENTIAL IMPACT OF PREVALENCE SHIFTS ON PROFIT MARGINS

Let’s assume for now that we expect overall mortality between the two triage paths to be equal in a given program. Let’s also



assume that premium rates are not differentiated by triage path. It might be tempting to assume that since overall mortality is the same and premium rates are the same, then the profit margin is the same for the two paths. This does not necessarily follow.

First, prevalence could shift toward the best class. If the underwriting rules are slightly looser on one side of the triage, then overall premium collected will be less in that path than through the other path if we held the applicants constant on both sides.

Secondly, overall mortality can be preserved even though risk class relative mortality and risk class prevalence could both shift. Consider the example in Chart 2.

Chart 2  
Impact of Class Shifts

Path 1		
Risk Class	Relative mortality	Prevalence
Best Preferred	85%	40%
Preferred	95%	30%
Standard	125%	30%
Overall	100%	100%

Path 2		
Risk Class	Relative mortality	Prevalence
Best Preferred	90%	50%
Preferred	105%	40%
Standard	130%	10%
Overall	100%	100%

In this example, the relative mortality for each risk class is worse in path 2 than path 1, but the overall mortality in each path is the same. This is due to the shift in the prevalence by risk class.<sup>6</sup> So even though overall mortality is preserved, the total premium collected<sup>7</sup> will decrease due to the shift toward preferred from path 1 to path 2. To demonstrate this, premiums are included in Chart 3, along with claim margin (calculated as mortality / premium). For each path, premiums are equal to 106 percent of path 1 class-level mortality.

Each class in path 1 is priced to have a 94 percent claim margin, meaning it is priced to have 6 percent of premium left over after accounting for claims. However, due to prevalence shifts, applying these same premium rates to path 2 results in a claim margin of 101 percent, leaving premiums insufficient to pay claims. So despite being mortality neutral, the two paths are not profit neutral.

Chart 3  
Impact of Class Shifts with Premium

Path 1				
Risk Class	Relative mortality	Prevalence	Premium	Claim Margin
Best Preferred	85%	40%	90%	94%
Preferred	95%	30%	101%	94%
Standard	125%	30%	133%	94%
Overall	100%	100%	106%	94%

Path 2				
Risk Class	Relative mortality	Prevalence	Premium	Claim Margin
Best Preferred	90%	50%	90%	100%
Preferred	105%	40%	101%	104%
Standard	130%	10%	133%	98%
Overall	100%	100%	99%	101%

## CONCLUSION

Triage systems within accelerated underwriting programs can impact both class prevalence and mortality, and both of these effects should be priced for. Each can independently impact profitability, and ignoring either one in pricing could compromise the viability of a program. ■



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## ENDNOTES

- [https://www.munichre.com/site/marclife-mobile/get/documents\\_E-375236011/marclife/asset.marclife/Documents/Publications/LexisNexis-Risk-Classifier-stratifying-mortality-risk-using-alternative-data-sources.pdf](https://www.munichre.com/site/marclife-mobile/get/documents_E-375236011/marclife/asset.marclife/Documents/Publications/LexisNexis-Risk-Classifier-stratifying-mortality-risk-using-alternative-data-sources.pdf)
- [https://www.munichre.com/site/marclife-mobile/get/documents\\_E2066913291/marclife/asset.marclife/Documents/Publications/Milliman-RX-Risk-Score-2.0-9-18-18.pdf](https://www.munichre.com/site/marclife-mobile/get/documents_E2066913291/marclife/asset.marclife/Documents/Publications/Milliman-RX-Risk-Score-2.0-9-18-18.pdf)
- Note: here, preferred composition refers to the distribution of classes a traditional underwriter would have placed, had they underwritten this population.
- This study has 2,715 claims.
- It would be naïve to expect to see the above results on a population without first understanding the relationship between LNRC and preferred criteria used to segment that population.
- Consider a closed universe of 1000 insurance applicants that are standard or better risks. No matter how you subdivide the group into various risk classes, the total mortality of that group does not change. However after determining a risk class for each individual you could arbitrarily decide to upgrade everyone by one class above their assessed fully underwritten class. In that case, the relative mortality of each non-empty class will be worse, but the total mortality does not change.
- Premium collected** =  $\sum_i$  Premium rates for class  $i$  \* Prevalence in class  $i$