Milliman LTC Advanced Risk Analytics™ (Milliman LARA™)

# Superior Predictive Performance of Milliman LARA Models

## Milliman LARA is a proprietary suite of predictive modeling solutions that help long-term care (LTC) carriers understand and manage individual LTC risk with risk scores and drivers, bringing insights through industry-leading data and models.

The Milliman LARA claim risk model is a machine learning model that assists LTC carriers in stratifying their population to proactively manage the health and claim activity of their most at-risk members. Paired with intervention programs that improve member health and ability to age-in-place, LARA risk scores are a key component to assist LTC carriers in reducing LTC claims cost through preventative approaches.

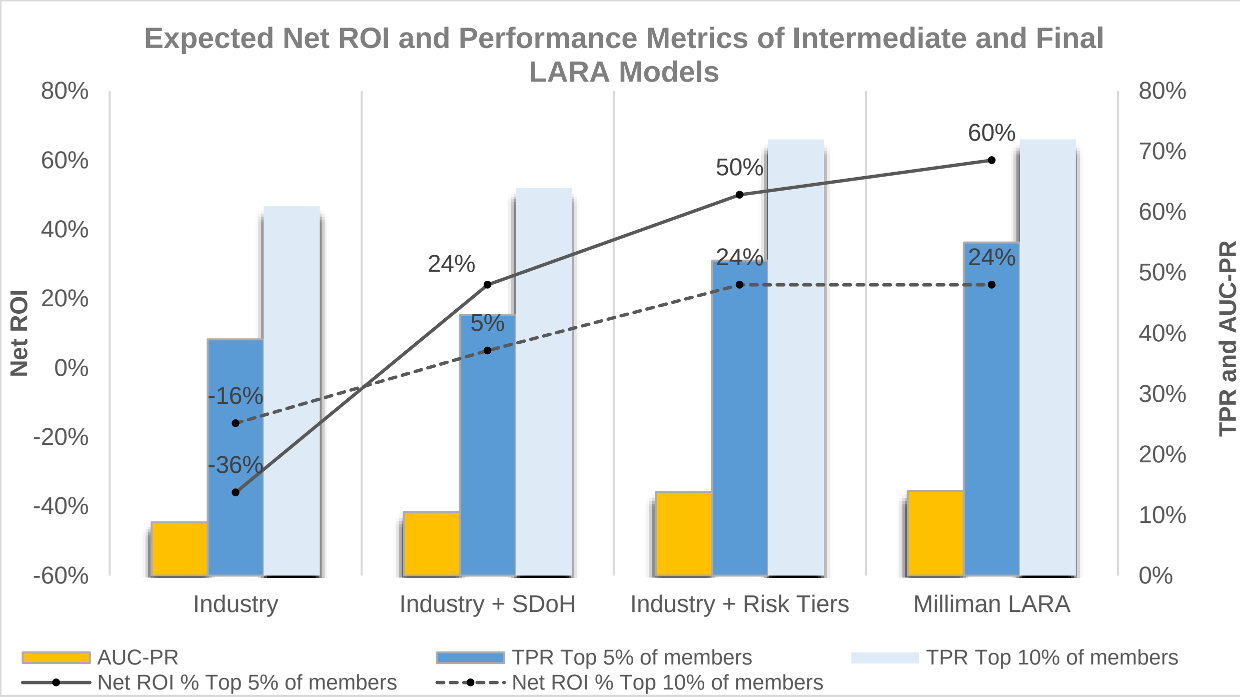
The LARA claim risk model has outstanding predictive performance not only because it uses a robust machine learning algorithm, but also because it is trained on a comprehensive industry dataset. The dataset includes information sourced from LTC carrier data, proprietary third-party consumer and social determinants of health (SDoH) data, and LTC risk tiers developed using Milliman IntelliScript® medical and pharmacy claim data[1]. The experience data used in training the LARA claim risk model has over 3 million life years of exposures.

We used state of the art predictive modeling techniques to train the model. We then performed an attribution analysis of model performance and expected return on investment (ROI) by expanding our dataset one source at a time. We analyzed the performance of models based on

1. LTC industry data (Industry)
2. LTC industry and SDoH data (Industry + SDoH)
3. LTC industry data and LTC risk tiers (Industry + Risk Tiers)
4. All three data sources (Milliman LARA). The attribution analysis allows us to understand the incremental impact each data source has on the model's predictive performance and expected ROI.

The following figure summarizes multiple performance metrics (described below) from our attribution analysis for models developed using the datasets described above. The Net ROI %'s shown in the figure are achieved by focusing prevention initiatives on the top 5% and 10% highest risk members identified by each model, respectively. Each model performance metric shows improvement as the dataset expands. The Milliman LARA model has the best predictive performance and Net ROI %.

[1] Milliman IntelliScript products are widely used for underwriting and segmentation in the insurance industry as a source of data and interpretation for medical claims and pharmacy histories. More information on IntelliScript can be found at https://www.rxhistories.com/




We analyzed the following metrics:

**Net ROI %** – To calculate the expected ROI, we performed simulated pilot analyses[2]. The Net ROI % metric can be viewed as a proxy for comparing costs versus benefits. We define Net ROI % as (savings less cost) divided by cost. Initially, as the proportion of the stratified population prioritized for intervention increases, the Net ROI % also increases. As this proportion continues to grow, the Net ROI % peaks and then begins decreasing, eventually becoming negative. Based on the assumptions included in our simulated pilots, a company can achieve 60% net ROI by providing interventions to the top 5% highest risk population, as identified by the LARA model. Alternatively, a company could provide interventions to as much as 13% of the highest risk members while still achieving a net ROI of at least 5%. Companies should consider their financial goals and resources when determining the optimal population to include in their intervention programs.

**True positive rate (TPR)** – The TPR is the proportion of actual claims correctly identified within the population tested. This metric is relevant to use in a care management setting, as companies will likely not have resources to implement interventions with every member in their population. Therefore, they can maximize the potential impact of their intervention program by reaching out to members that have the highest probability of claim. The overall goal is to increase the number of actual claims identified within the high risk strata (true positives), while at the same time, realizing that resource constraints limit the total number of members that can be included in the program. In our simulation, the LARA model identified 55% of total claims within the stratified top 5% highest risk members and 72% of total claims within the stratified top 10% highest risk members.

**Area under the curve precision recall curve (AUC-PR)** – The AUC-PR is a common way to summarize a model's overall performance, which focuses on successful positive predictions and ignores successful negative predictions (i.e., no claim). With an imbalanced dataset like LTC claim incidence, the AUC-PR is a more meaningful metric to assess a model than the area under the receiver operating characteristic curve (AUC-ROC), another common metric to summarize a model's performance. When the dataset is imbalanced, the AUC-ROC metric can be misleading

[2] As an example of the methodology, we followed a similar approach to calculate the expected ROI as detailed in this simulated pilot: https://www.milliman.com/-/media/products/lara/12-10-21-milliman-lara_simulated-pilot-case-study.ashx

when a model correctly predicts a large number of true negatives (i.e., no claim), but does not provide meaningful insights into the high-risk population.

Intelligence from the LARA model can be used to stratify policyholders within LTC wellness programs so that the programs can be refined to provide more appropriate levels of outreach and support based on each member's estimated risk level. To ensure this is done equitably, it is important to test the model to determine whether there is evidence of unfair bias toward any racial or ethnic group. We define unfair bias as individuals with the same health status being less likely to be prioritized for intervention due to their race or ethnicity. Because race and ethnicity were not explicitly included our dataset, we used multiple algorithms to impute the race or ethnicity of each member. We then analyzed the model results by imputed race and ethnicity for potential unfair bias. From these analyses, we did not find evidence to support the hypothesis that the predictions from the LARA model would contribute to an individual being unfairly excluded from an intervention program based on their race or ethnicity. We will continue to monitor for unfair bias in future iterations of the model as more data is available and model refinements are implemented.

LARA model development strictly follows Milliman's rigorous Quality Risk Management guidelines. Model development and results have been extensively peer reviewed by numerous actuaries, data scientists, and LTC subject matter experts throughout the various stages of development.

Milliman **LARA**

Milliman Long-term care Advanced Risk Analytics™ (Milliman LARA™) leverages the industry-renowned expertise of Milliman consultants to uncover powerful insights about your LTC population. It uses predictive analytics, LTC claims data, and proprietary data sets to identify your high-risk policyholders before they reach severe stages of LTC needs. Early intervention empowers you to drive better health outcomes—improving a policyholder's quality of life by helping them age in place. Using a focused solution to these interventions drives ROI.

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