Milliman LTC Advanced Risk Analytics™ (Milliman LARA™)

# Long-term care wellness initiatives: A simulated pilot program

Pre-claim interventions can be an effective method to improve health outcomes, reduce severity of future claims, and reduce overall long-term care claim costs. A simulated pilot study illustrates that this can be accomplished on a stratified population with positive return on investment.

## Summary


Wellness and intervention programs have been an important and successful tool used in other lines of business for the benefit of the insurance consumer. We performed a simulated pilot to explore whether similar programs for long-term care (LTC) consumers also have the potential to generate positive return on investment (ROI) for insurance carriers. We found that these programs can both help consumers and generate ROI for carriers, and that it was critical to use a highly predictive model to stratify the population. The predictive performance of the model was significantly increased by using personalized third-party data.

Milliman LTC Advanced Risk Analytics™ (Milliman LARA™) is a proprietary suite of predictive modeling solutions that focuses on early identification of potential LTC claimants to prioritize them for interventions aimed at preventing claims, delaying their need to utilize LTC services, and/or reducing the severity of services needed. We performed a simulated pilot to measure the effectiveness of the LARA models and the potential ROI of a focused wellness initiative for LTC policyholders. We tested the predictive performance of the LARA models against an out-of-time holdout sample for one LTC carrier. Using conservative assumptions for program costs and potential claim savings, our simulated pilot illustrates that wellness and intervention programs for LTC are sustainable and able to generate positive ROI.

Using LARA models, which utilize proprietary personalized variables derived from third-party data sources (e.g., consumer marketing and social determinants of health data), along with medical and prescription drug data from Milliman IntelliScript®, we stratified the highest risks in the holdout sample based on short-term claim likelihood. The stratified subgroup of policyholders we identified as having the highest risk of needing LTC services included over 75% of the actual claims incurred for insureds under age 90 within the holdout sample over the first 12 months. Having a model that is highly predictive is key, as it allows carriers to either increase ROI or maximize the population included in the program while still generating a minimum sustainable ROI level. Using conservative assumptions, we estimated potential savings of 1.0% of total incurred claim dollars, and positive net ROI exceeding 50% using a small cohort representing the top 6.5% of the total individuals most at risk of needing LTC. In this case study the cohort could be expanded to 13.5% of the population and still generate a minimal positive ROI.

Third-party data is critical to improving the predictive performance of the LARA models and achieving positive ROI. Our study showed that baseline models that only relied on data from the insurance carrier had much lower predictive performance and no ROI. These results suggest that the inclusion of LARA's proprietary third-party data sources is a key driver of positive ROI as they dramatically improve the predictive performance of the LARA models. This increases potential savings and ROI, along with the number of policyholders who could benefit from a sustainable wellness initiative. We anticipate additional improvements in model performance once industry data from more historical LTC insurance policyholders are integrated into the LARA models.

## Alice's story

Consider an elderly woman—let's call her Alice—who purchased an LTC policy in 2006 when she was 65 years old. At that time, Alice was very healthy and had recently taken an early retirement and moved from Minnesota to Arizona with her spouse. Through underwriting, her LTC insurance carrier knew something of her health status, marital status, and residency. In the 15 years since she bought the LTC policy, however, her life has changed significantly.

Alice's spouse passed away in 2017 and she subsequently moved back to Minnesota to be closer to her family. Due to the COVID-19 pandemic and resulting restrictions, she has been struggling with social isolation. She was prescribed an antianxiety drug that may increase her risk of falls as a side effect.

While her LTC insurance carrier is aware of Alice's move to Minnesota (the insurer sends premium collection bills to her physical address), the insurer has likely missed key events that suggest Alice may now be at a higher risk of an LTC claim. In addition to public census or geographic data, proprietary third-party data can be used to help identify this risk. These data sources may indicate that Alice is now living in a location prone to snow and ice in the winter, that her medical and pharmacy histories indicate an increased risk of an LTC claim, and that she is now living alone. By collecting and aggregating this third-party data with LTC insurance industry data, insurance carriers can use LARA models to identify Alice as a strong candidate for outreach and intervention to potentially avoid or delay a high-severity LTC claim.

Once Alice is identified as having a high risk of claim by the LARA models, a vendor providing aging-in-place interventions can reach out and provide services to help Alice. An initial assessment can confirm (or further clarify) the risks identified by the LARA models and then the vendor can provide or coordinate additional support. Simple steps can help mitigate Alice's fall risks such as informing her of the potential fall risk as a side effect of her medication and asking her to discuss this with her doctor, or performing a review of her house (either in person or virtually) to assess risk factors and then suggesting and coordinating updates such as grab bars. Helping Alice find social activities can alleviate social isolation. Educating both Alice and her family on potential risks and ways to mitigate them can increase Alice's overall well-being and independence, helping her remain in her home longer.

Appendix A provides additional background regarding LTC wellness initiatives, including further detail on Milliman LARA and information on The Helper Bees' Care Concierge program. Milliman and The Helper Bees have a strategic alliance to provide a single, comprehensive, and actionable solution to carriers for the design, implementation, and evaluation of focused LTC wellness programs. Additionally, LARA intelligence can be used in conjunction with any wellness or intervention provider.

## A simulated pilot

The effectiveness of an LTC wellness initiative, such as the outreach and interventions we imagined for Alice, could be evaluated using a pilot program that bifurcates the population into a test group and a control group.

Pilot programs require careful planning and implementation so that analytics can be developed to accurately measure success. This process takes time to set up, monitor, and measure. Additionally, depending on the size of the populations included in the pilot, it may take multiple years for credible experience to develop, from which an insurance carrier could judge the success of the program.

As an alternative approach to measure potential costs and savings, in addition to testing the predictive performance of the LARA models, we developed a simulated pilot based on the data of a single LTC insurance carrier. We used the results of this simulation to estimate the potential costs, savings, and ROI of a focused LTC wellness initiative based on LARA intelligence.

The simulated pilot can be helpful in illustrating the business case for a pilot program and creating a benchmark to monitor future results and expectations. The simulation can estimate the potential implications for an entire block before implementing a full pilot and outreach program and incurring the associated costs. It can also be used to explore the potential impact of implementing a wellness initiative on specific subsets of a carrier's LTC products.

**ANALYSIS**

With a carrier's permission, we built customized LARA pre-claim models using various data sources for a block of approximately 85,000 active (pre-claim) LTC insureds.

We trained the models using the carrier's historical experience data through 2018. We then used the LARA models to calculate risk scores for all active insureds as of yearend 2018 and ranked (stratified) the risks of the population to prioritize interventions for those with the highest estimated risk of claim. After stratifying the population, we compared predicted claims against actual claims incurred during calendar year 2019 (the out-of-time test holdout). We used the comparison to actual incurred claims, in conjunction with a conservative range of assumptions for potential savings and intervention costs, to estimate a range of potential results over the first 12 months of the simulated pilot program.

We estimated savings due to three different intervention outcomes: prevented claims, delayed home health care claims, and facility claims shifted to home care prior to transitioning to a facility. Cost assumptions included direct costs for Milliman LARA analyses and fees, along with estimated costs for interventions performed by a wellness provider. We assumed that these costs are paid by the carrier, while any additional costs (e.g., handrail installation) are paid by insureds out of pocket or by Medicare, rather than being part of their LTC policy benefits. Net ROI was defined as: (savings less costs) divided by costs. Both cost and savings assumptions varied for insureds under age 90 versus those ages 90 and older; no savings were assumed for insureds age 90 or older.

To test the impact of third-party data on the performance of the models, we first developed a baseline model that included only data that was collected from the carrier. This included variables related to the insureds' demographics (e.g., attained age and gender), policy characteristics (e.g., daily benefit amount and lifetime benefit period), and historical policy experience (e.g., prior claims and changes in benefits). We then developed the LARA models that included additional proprietary personalized variables derived from third-party data sources, along with medical and prescription drug information from Milliman IntelliScript.

The third-party data is collected from various sources, including from external data partners, using personally identifiable information (PII) to obtain additional information on each insured, such as living alone status and other consumer marketing and social determinants of health data that may not be available to carriers.

For our pre-claim LARA models, we have developed LTC risk tiers in conjunction with Milliman IntelliScript using medical diagnosis and prescription drug information. The LTC risk tiers are calculated using a predictive model on de-identified medical and prescription histories. The LTC risk tier that corresponds to a specific individual is then reidentified and returned without protected health information (PHI). HIPAA authorizations are not required for the pre-claim LARA models because PHI is not exposed during this process (i.e., member-specific drug and diagnosis data is not returned). The LTC risk tiers are developed using a structure similar to the Milliman IntelliScript Curv® product, which has been used in the healthcare space to stratify populations for hundreds of carriers.

**RESULTS**

Due to the low frequency of LTC claims, determining the portion of the population prioritized for intervention is key to ensuring a sustainable program (measured by a positive ROI) as part of an LTC wellness initiative. Applying the interventions to a population that is too large or that is too old, on average, to generate savings, will result in program costs that exceed savings. A highly predictive model allows you to help the maximum number of individuals while still returning a goal ROI.

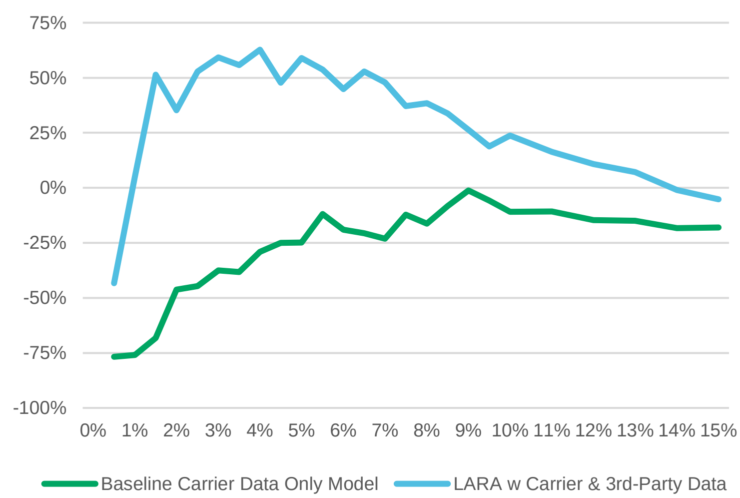
When prioritizing ROI, our analysis suggests a net ROI of over 50% (i.e., savings exceed costs by over 50%) is achievable when using the LARA models in a conservative scenario. Less pessimistic scenarios suggest potential ROI exceeding 150% may be possible. Maximizing ROI requires implementing interventions on a smaller subset of the population. A sustainable program that generates lower, yet still positive, ROI can also be developed where a larger subset of the population is prioritized for intervention.

In contrast, the models based on carrier data only generated negative ROI in our conservative scenario. This is because the baseline carrier data-only models produce a high-risk population that is older, on average, than the LARA models and we assume that no savings can be generated for insureds age 90 and older.

Figure 1 illustrates the estimated ROI for both the baseline models and the LARA models across a range of prioritized populations.

Due to the low frequency of LTC claims, determining the portion of the population prioritized for intervention is key to ensuring a sustainable program as part of an LTC wellness initiative.

**FIGURE 1: ESTIMATED NET ROI PERCENTAGE BY PRIORITIZED POPULATION PERCENTAGE – CONSERVATIVE SCENARIO**



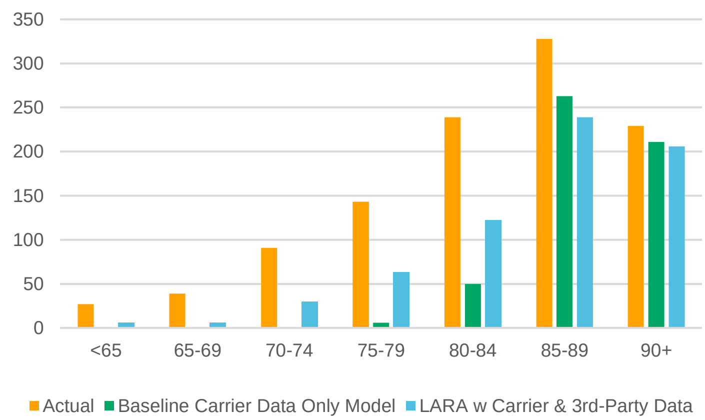

As illustrated in Figure 1, the baseline models without third-party data are unable to generate positive ROI, although they nearly break even with a prioritized population of approximately 9.0%. The net ROI dollars are maximized at a 6.5% prioritized population with the LARA models. Using these more predictive LARA models would also allow a carrier to prioritize a larger population of up to 13.5% of the most high-risk individuals while still generating positive ROI. Larger ROIs are projected under less conservative scenarios, driven by both less pessimistic assumptions and larger prioritized populations. These larger ROIs in less conservative scenarios would allow carriers to prioritize an even larger population for intervention while still producing positive ROI as part of a sustainable program. Because our analysis was based on conservative (pessimistic) assumptions, we believe these materially larger ROIs and prioritized populations are achievable.

As can be seen in Figure 1, the addition of the proprietary third-party data dramatically increases the estimated net ROI, even in our conservative scenario. The inclusion of this data allows the LARA models to predict a higher proportion of claims at younger ages, for which we assume interventions are more effective. However, when using such third-party data in models, it's important to consider how certain variables may introduce bias into the predictions. Specifically, bias that may lead to unfair discrimination towards a protected class. Therefore, it is important to place extra consideration on potential sources of bias when developing and selecting variables used in the models. In addition to being thoughtful about the variables included in the models, it is also important to test the models for unfair discrimination before putting them into production. Milliman has tested several predictive models used in the healthcare space for potential bias, including the Milliman Advanced Risk Adjusters™ (MARA™) models.[1]

[1] Rode, E. & Leida, H. K. (September 2020). Testing Milliman Advanced Risk Adjuster Models for Racial Bias. Milliman Report. Retrieved December 10, 2021, from https://www.milliman.com/en/insight/testing-milliman-advanced-risk-adjuster-models-for-racial-bias-medicare-model-results#.

Figure 2 shows the total actual claims in the holdout data (i.e., those incurred in 2019) as well as the claims correctly predicted within the prioritized populations in the baseline models using carrier data only and in the LARA models that use both carrier and third-party data.

**FIGURE 2: CLAIMS IDENTIFIED IN PRIORITIZED POPULATION BY ATTAINED AGE BAND**




Note: Different subsets of the total population are prioritized by each model when selecting cohorts of identical size.

As illustrated in Figure 2, the inclusion of third-party data improves the predictive capabilities of the LARA models, especially at younger attained ages, where we believe interventions are more effective. The two sets of models illustrated in Figure 2 select a same-sized cohort of policyholders, but identify different subsets of the population, as the models stratify the high-risk population differently.

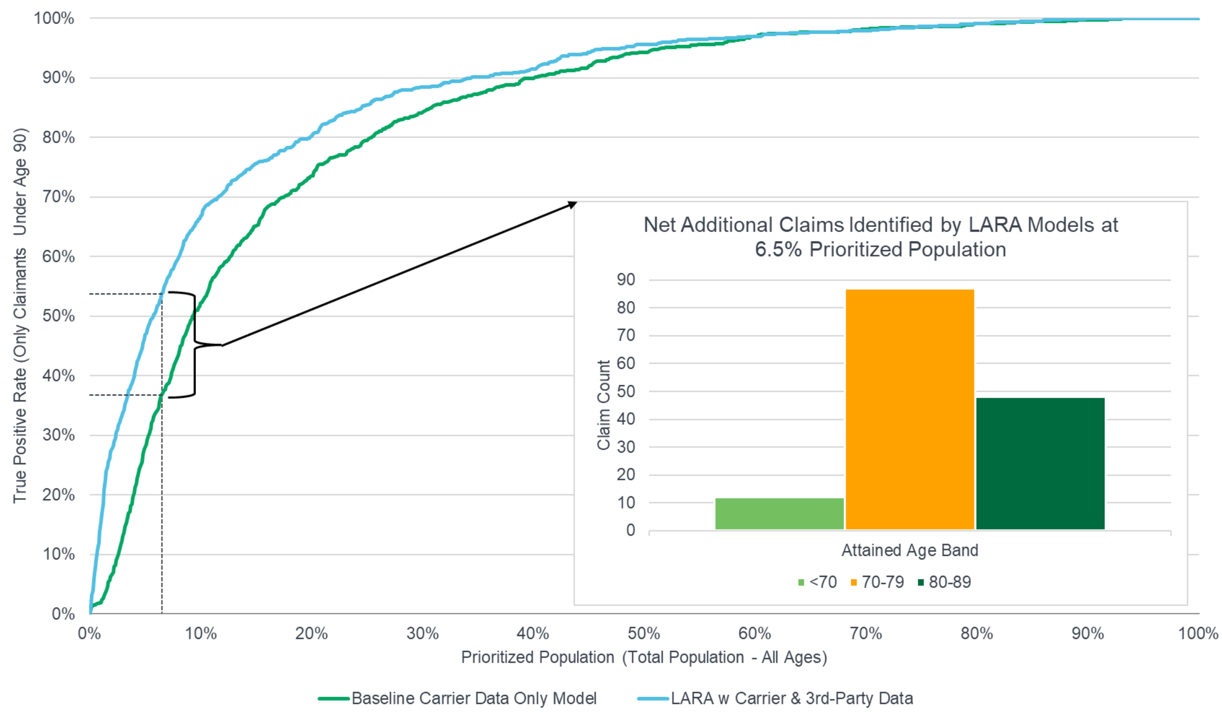
The LARA models classify additional younger claimants as high-risk while classifying fewer older claimants as high-risk within the prioritized population. Compared to the baseline models using carrier data only, the LARA models correctly predict nearly 150 net additional claims under age 90 and 140 net additional claims in total. The identification of additional claims at younger ages in the LARA models results in additional ROI and/or the potential to expand the outreach population. This is further illustrated in Figure 3 below.

As discussed previously, determining the portion of the population prioritized for intervention is key to ensuring positive ROI as part of an LTC wellness initiative. An intervention program applied to a population that is too large or one in which interventions will not be effective will result in program costs that exceed savings. Models that predict a high percentage of claims when prioritizing a subset of the total population, such as the LARA models, can be used to refine the population prioritized for an intervention.

> The identification of additional claims at younger ages in the LARA models results in additional ROI and/or the potential to expand the outreach population.

Figure 3 illustrates the percentage of claims correctly identified (i.e., the true positive rate) for insureds under age 90 by the baseline carrier data-only models and by the LARA models for varying percentages of the total population. Including all insureds increases the true positive rates as both sets of models are also highly predictive for insureds age 90 and older. However, because we assume that interventions are not effective for insureds age 90 or older, they are excluded from Figure 3.

**FIGURE 3: TRUE POSITIVE RATE BY PRIORITIZED POPULATION PERCENTAGE WITH BREAKOUT OF NET ADDITIONAL CLAIMS IDENTIFIED BY LARA MODELS AT 6.5% PRIORITIZED POPULATION**




As can be seen in Figure 3, when 6.5% of the total population is prioritized for intervention, the LARA models utilizing proprietary third-party data identify 54% of claimants under the age of 90, compared to only 37% when the baseline models based on carrier data only are used. This results in nearly 150 additional net claims under age 90 correctly identified by the LARA models, with many of those at younger ages, as seen in Figure 2 above.

The 6.5% prioritized population is the level at which we estimate the maximum ROI is achieved under our conservative assumption scenario. Less pessimistic scenarios show larger positive ROIs with larger prioritized populations. As shown in Figure 3, the true positive rate for insureds under age 90 exceeds 75% when less than 15% of the total population is prioritized. The high percentage of incurred claims for younger ages achieved when prioritizing a subset of the total population allows for a sustainable LTC wellness initiative that benefits a large portion of LTC claimants.

## ASSUMPTIONS

Because the results of our analyses are simulated, rather than an actual pilot, we have utilized a range of conservative (pessimistic) assumptions. While the results illustrated here represent our most conservative scenario, we tested a range of assumptions of varying levels of conservatism. More pessimistic assumptions reflected less savings and higher costs associated with the interventions, while less pessimistic assumptions reflected higher savings and lower costs.

The assumptions used in our analyses were extrapolated from the actual experience observed by The Helper Bees. The goal of our analysis was to demonstrate that, under conservative assumptions, positive ROIs were achievable as part of a sustainable LTC wellness initiative. We found that, even under conservative assumptions, the simulated pilot generated positive ROI. We believe that larger ROIs are achievable as part of real-world programs, where certain conservative assumptions included in our analyses would be replaced with actual results.

Additional detail regarding the assumptions used in the analysis can be found in Appendix B.

## Limitations and qualifications

Jeff Anderson, Robert Eaton, and Missy Gordon, the authors of this analysis, are consulting actuaries for Milliman. They are members of the American Academy of Actuaries and meet the qualification standards of the American Academy of Actuaries to render the actuarial opinion contained herein.

This analysis was not prepared solely for any single company. Milliman does not intend to benefit or create a legal duty to any recipient of this information.

In preparing this analysis, we have relied on data and other information provided to us by a client carrier and our third-party data sources. If the underlying data or information is inaccurate or incomplete, the results included in this analysis may likewise be inaccurate or incomplete. We have performed a limited review of the data used directly in our analysis for reasonableness and consistency, and have not found material defects in the data. If there are material defects in the data, it is possible that they would be uncovered by a detailed, systematic review and comparison of the data to search for data values that are questionable or for relationships that are materially inconsistent. Such a review was beyond the scope of this analysis.

We have developed certain models to estimate the values included in this analysis. The intent of the models was to estimate future experience. We have reviewed the models, including their inputs, calculations, and outputs, for consistency, reasonableness, and appropriateness for the intended purpose and in compliance with generally accepted actuarial practice and relevant actuarial standards of practice. The models, including all input, calculations, and output, may not be appropriate for any other purpose.

Differences between our estimates and actual amounts depend on the extent to which future experience conforms to the assumptions made for this analysis. It is certain that actual experience will not conform exactly to the assumptions used in this analysis. Actual amounts will differ from estimated amounts to the extent that actual experience deviates from expected experience. To the extent that actual savings are lower or actual costs are higher, actual returns on investment will be lower than those estimated as part of this analysis.



**CONTACT**

LARA@milliman.com

# Appendix A: LTC wellness and intervention

## Background

### PROBLEM

The need for LTC services in the United States is projected to increase significantly in the future as a larger portion of the general population will be older than 65 and the number of individuals over age 85 is expected to triple.[2] Private LTC insurance carriers are aware of this problem and have issued LTC policies to help meet this need, providing valuable protection for this risk. However, as the industry has matured, we have seen that this risk was originally underpriced.

Carriers have been mitigating this underpriced risk for more than a decade by increasing both premium rates and reserves. Many carriers are now looking for ways to manage future claim costs as an additional mitigation approach. Focused wellness intervention programs can provide an efficient option to help mitigate this risk, while also improving the health and wellness of policyholders. By prioritizing the population with the highest risk of an LTC claim in the near future, carriers can achieve positive ROI for these wellness programs. However, evaluating claim risks and measuring the effectiveness of wellness intervention programs is hard.

Charges for LTC services received in assisted living and skilled nursing facilities are generally higher than those for services received in a home care setting. The higher prices are most often due to the higher severity (i.e., worse health) of claimants who need care in facilities compared to those who receive care in their homes. Aging-in-place intervention programs like The Helper Bees' Care Concierge can generate claim savings by preventing or delaying claims, or by shifting more services from a facility setting to a home care setting. When intervention programs are paired with policyholder intelligence such as that generated by Milliman LARA, the program can be focused on the most at-risk insureds and produce positive ROI for the carrier.

Consumers prefer to remain in their homes as long as possible, but they may be unable to do so if their homes are unfit or ill-equipped for aging-in-place. Additionally, individuals and their support systems may not realize that they are at risk, or they may not be aware that there are resources and services available to help them stay in their homes. In addition to potential hazards within the home, there may also be other risks that could be mitigated. For example, side effects from certain prescription drugs or interactions between drugs can pose a fall risk for elderly individuals. We believe there's a strong opportunity to increase awareness and education of these potential risks, including the actions individuals can take to be safer and live more independently. Additionally, there are many technology companies that have produced products that assist the elderly with monitoring and reducing social isolation, and these products can improve the health and well-being of the elderly.

Historically, insurance carriers have used post-claim care management programs to manage claim costs. After claims have occurred, carriers manage them to prevent fraud, waste, and/or abuse, but little has been done—and it is difficult—to prevent a claim. While denying a claim will reduce cost, it does not improve the health of consumers and many in society may harbor negative views of insurers that do so, even if the denial is valid (e.g., it can be viewed as big insurance companies taking advantage of the elderly or doing whatever it takes to avoid paying claims). While avoiding fraud, waste, and abuse is important for carriers, pursuing additional options to manage cost that also align the incentives of carrier (lower cost) and consumer (better health) is beneficial to insurers, consumers, and society.

[2] Ortman, J.M., Velkoff, V.A., & Hogan, H. (May 2014). An Aging Nation: The Older Population in the United States. Current Population Reports, P25-1140, U.S. Census Bureau. Retrieved December 10, 2021, from https://www.census.gov/prod/2014pubs/p25-1140.pdf.

## OUR SOLUTION

We believe that wellness intervention programs can generate claim savings by preventing or delaying claims, or by shifting more claims from a facility setting to a home care setting. When wellness intervention programs are paired with advanced predictive analytics, the program can be focused on the most at-risk insureds to benefit the largest number of policyholders who actually need support, while also producing positive ROI for the carrier.

Milliman's LARA product and strategic alliance with The Helper Bees can help carriers improve the overall health of their insured populations and reduce total claim costs.

### Milliman: LARA

LARA is a proprietary suite of predictive modeling solutions that focuses on early identification of potential and current LTC claimants to prioritize them for interventions aimed at preventing claims, delaying their need to utilize LTC services, and/or reducing the severity of services needed.

The LARA pre-claim models provide reports to carriers that allow them to stratify the non-claimant (i.e., active) population into groups based on relative future claim risks. This stratification enables carriers to optimize the outreach for interventions, which may mitigate the incidence or severity of LTC claims. We are also developing on-claim models, which can help carriers support existing home health care claimants in their homes and delay or prevent their transfer into a facility.

The LARA suite of predictive modeling solutions is based on LTC industry data gathered specifically for this purpose. The models can also be recalibrated on a carrier's data to reflect unique characteristics of the carrier's insured population and/or available data points.

The LARA models also utilize PII to obtain additional predictive information from third-party data vendors. These vendors provide additional data fields, such as living alone status, which may not be available to carriers, that we believe may be predictive of near-term future LTC claim experience. In addition to information from our external data partners, the LARA models also harness LTC risk tiers developed in conjunction with Milliman IntelliScript using medical diagnosis and prescription drug information. While the focus of most LTC experience studies and projection assumptions is expected long-term future experience, LARA's focus is near-term experience. This near-term focus enables the use of alternate variables such as current marital status, which may not be predictive or viable for use in the development of long-term projection assumptions.

Milliman consultants are industry leaders with decades of subject-matter experience supporting carriers in managing LTC risk. This includes data analysis, assumption development, and modeling for LTC insurance. With this expertise and understanding of the LTC industry, Milliman is uniquely positioned to analyze the data being collected and develop powerful predictive models to identify insureds at high risk of LTC claims.

Milliman's strategic alliance with The Helper Bees allows carriers to convert the actionable information produced by the LARA models into real-world outreach and interventions to improve the health and wellness of their customers. LARA intelligence can also be used by carriers in conjunction with other wellness providers.

### The Helper Bees: Care Concierge

The Helper Bees' Care Concierge program provides care coordination benefits to help improve the health of insureds and delay the use of LTC facility services. Improving health and increasing independence can also decrease the severity of LTC claims. These efforts can then lead to reduced overall LTC claim costs.

The Care Concierge program is comprised of two equally important foundational components, educational content and expert guidance. When deployed together, it is possible to prioritize and improve the overall wellness of both the claimant and non-claimant populations. The program's approach educates non-claimants and empowers them to make wise care decisions while also guiding claimants to solutions that enable aging in place.

By design, the Care Concierge team does not know the benefits provided by any insured's LTC policy. This allows the team to focus on improving the health of each insured, not on maximizing the potential benefits payable under an LTC policy.

In a continued effort to provide high-quality solutions to insureds, The Helper Bees recently launched an aging-in-place marketplace. Using the marketplace, the Care Concierge specialist can provide a recommended plan of care using the in-home care and support service available through the marketplace's vetted providers.

Each insured's interaction and utilization data is analyzed and delivered back to the carrier for unprecedented insight into policyholder behaviors, needs, and the potential interventions necessary to delay institutionalization. These insights can also be leveraged by all parties (carrier, Milliman, and The Helper Bees) to tailor initiatives or programs and refine models focusing on high-risk policyholders.

### Results

Combined, Milliman LARA and The Helper Bees can help carriers effectively manage their non-claimant and claimant populations and reduce future overall LTC claim costs. In addition to generating goodwill and improving the health of insureds, the savings in claim dollars outweigh the costs of LARA and the Care Concierge program and can generate positive ROI for carriers.

In the past, many carriers have been concerned that outreach to insureds may incite the incurral of claims by reminding insureds of their policy and benefits. Due to the near ubiquitous rate increases over the last decade, we believe this risk to be reduced for most carriers. Additionally, a goal of the LARA intelligence and Care Concierge program is to reduce facility claims. A small increase in total claims would be overshadowed by a shift in incidence from facility to home health care claims.

## Additional detail

### MILLIMAN: LARA

The LARA industry models are currently being developed using LTC experience data collected from carriers that are supporting these important wellness initiatives.

The models utilize various data sources to give carriers the option to select the information that feeds the LARA models' intelligence. These data sources give the carrier the option to include various proprietary personalized third-party data sources (e.g., consumer marketing and social determinants of health data) along with LTC risk tiers developed from medical and prescription drug information from Milliman IntelliScript. While these personalized data sources come at an additional cost, our analyses indicate they provide significant improvements in model predictivity, which is necessary to generate positive ROI for carriers. More importantly, it can also help identify more insureds who need extra care to stay in their homes longer.

In addition to the LARA industry models, carriers can also choose to have the models customized to specific blocks of business or to incorporate additional unique data sources a carrier may have in-house. This customization has the potential to improve the predictive performance of the LARA industry models even further.

Milliman has a long history of partnering with the LTC industry to support carriers as they manage their blocks of LTC policies. As mentioned above, Milliman is collaborating with multiple carriers to expand the industry data set that will be used as the base for the LARA models and future expansions. This collaboration also includes understanding the various risks and considerations for developing and implementing a wellness program. Milliman can support carriers as they pilot the concept and communicate to policyholders, while also supporting the development of an efficient pipeline of data and information that can be returned into the LARA models to expand and enhance them for improved future risk analysis and program monitoring.

Because the LARA models will be regularly refined and available third-party data is frequently refreshed, we expect the pre-claim models will provide actionable findings for varying cohorts of high-risk insureds as frequently as quarterly. Quarterly intelligence updates will ensure that intervention efforts are always focused on the most high-risk insureds. Carriers may also choose to utilize LARA intelligence less frequently, such as annually. To maximize the benefit of LARA intelligence, carriers will need to provide their current insured population data, including PII, and allow Milliman to work with our third-party data partners to collect additional data.

LARA intelligence output includes a seriatim listing of high-risk insureds. This listing will include claim probabilities and risk drivers (e.g., medical/pharmacy risk tier, socioeconomic status, etc.). Potential future expansion may also include an estimate of the potential cost of claim for each individual, along with claim preventability, outreach receptivity, and intervention receptivity scores; and intervention action indicators (i.e., what types of interventions may be beneficial for each insured). Output can be customized to prioritize a certain percentage of the active population to maximize total claim savings, to maximize ROI, or to maximize the population prioritized for intervention while still generating positive ROI. While not included in the standard LARA output, savings estimates or simulations and ROI analyses could also be prepared.

By focusing on the high-risk population, carriers are able to use their resources to deploy effective interventions to the insureds who are likely to benefit most. The seriatim detail provided with the LARA intelligence output, including drivers of risk, allow for customized and focused interventions.

After receiving the LARA intelligence, carriers can proceed with focused outreach. To estimate actual savings, some carriers may elect to perform a pilot using a control group, while others may prefer to perform outreach to the entire cohort of high-risk insureds identified by LARA to maximize savings and the number of individuals who benefit from the program.

Outreach may take several different forms, including mailers (postcards, letters, etc.), emails, or phone calls. Carriers can utilize existing staff or external vendors to support this outreach. Milliman and The Helper Bees can also aid carriers in drafting outreach materials, if desired. Helpful topics to use in the outreach include local services, meal delivery services, and home modifications to support overall wellness and promote independence while aging in place.

### THE HELPER BEES: CARE CONCIERGE

The Helper Bees' Care Concierge program was originally developed to help manage care for existing claims and is well suited to also provide support for pre-claim management. For a fixed monthly fee, the Care Concierge program works with insureds to identify care needs and potential providers. The goal of the Care Concierge program is to promote interventions to allow the claimant to remain at home and delay or prevent transition to facility care.

For the non-claimant population, the Care Concierge program can be implemented to provide services similar to those for active claimants, but with less frequent outreach. For insureds who need additional support, identified through an assessment, a plan of care can be developed. Services could take the form of aid in purchasing durable medical equipment (e.g., grab bars) or organizing transportation services. These services may be covered by Medicare or Medicare Advantage or paid out of pocket by insureds. In this case, the benefits could be provided without cost to the LTC insurance carrier or being deducted from an insured's LTC policy benefit.

The Helper Bees also offers an online platform that provides educational content to help insureds. As the policyholder engages with this content, the online platform delivers additional personalized content based on what they have already consumed. As the insured engages with the content, appropriate interventions can be developed for them. These interventions can be started by the insured contacting a Care Concierge expert after they have read content provided to them. Alternatively, the Care Concierge expert can reach out to the insured, once they see what materials are being consumed, and review additional information provided by the insured.

One goal of the initial outreach is to direct insureds to an online portal where they can find important information or connect with an expert. The portal allows for a personalized action plan to be created to accomplish the needed interventions. By bringing interactions online, insured behavior can be more easily monitored, providing valuable feedback to the carrier and The Helper Bees. This consumer behavioral information could also be incorporated into future refinements of the LARA predictive models.

After initial outreach via direct mail, outreach via phone can be used to provide information to insureds about the program and perform a preliminary assessment. Assessments could also be performed using an online survey. The assessments can be used to determine whether additional services may be helpful to support the insured remaining in the home.

# Appendix B: Assumption detail

## General assumptions

### POLICYHOLDER BEHAVIOR

Certain assumptions were developed in conjunction with The Helper Bees based on its experience with the on-claim Care Concierge program, which focuses on home health care claimants. These assumptions include the opt-out rate and the enrollment success rate. Additional detail regarding the Care Concierge program is included in Appendix A above.

Outreach will not be successful for a certain portion of insureds, because they are not interested in talking to a representative of the carrier, they do not believe they need support and do not respond, or available contact information is not accurate. In an on-claim program that focuses on home health care claimants, such as Care Concierge, there will also be a segment of the population who is not eligible (e.g., they are no longer on claim or have already moved into a facility). The Helper Bees has observed a combined rate of unreachable and ineligible claimants of approximately 40% as part of its on-claim Care Concierge program. Of the population that is reachable and eligible, a portion is expected to actively opt out of any intervention program. The Helper Bees has observed an opt-out rate of approximately 10% in the Care Concierge on-claim program (i.e., one-sixth of the eligible and reachable population), while successfully enrolling approximately 50% of claimants.

We bifurcate the prioritized population into two groups, those under age 90 and those age 90 or older, as we assume interventions for claimants age 90 or older will not be effective. The population under age 90 is then further split using various enrollment assumptions.

Based on The Helper Bees' experience, we assumed an opt-out rate of 10% and a successful enrollment rate of 50% of the total prioritized population under age 90 in our conservative scenario. We assumed the remaining 40% of this subpopulation were unreachable or ineligible (e.g., already in a facility). Our third-party data sources include multiple forms of contact information for both individuals and their family members. We believe that LARA intelligence can decrease the rate of unreachable policyholders and increase the total engagement percentage for a pre-claim intervention program. We performed sensitivity tests by decreasing the successful enrollment rate to estimate the minimum levels needed to generate positive ROI. These tests support positive ROI with a successful enrollment rate of 33% in the conservative scenario, decreasing to less than 30% in less pessimistic scenarios.

### PRIORITIZED POPULATION AND ROI CALCULATION

In our analyses, we assumed that the percentage of the population prioritized for the wellness initiative is selected to maximize the net ROI dollars. Under more conservative assumptions, a smaller prioritized population is needed to maximize ROI. As we reduce conservatism in the assumptions in less pessimistic scenarios, the prioritized population can be expanded while increasing ROI at the same time. This would allow a carrier to help a larger number of policyholders, while also generating positive ROI. In the most conservative scenario, we prioritized the top 6.5% of the population based on the predicted claim probability to maximize the net ROI dollars. Alternatively, carriers can expand the prioritized population to maximize the number of policyholders benefiting from a wellness initiative while targeting a sustainable ROI. While the net ROI dollars are maximized at a 6.5% prioritized population, a larger population up to 13.5% can be prioritized for the wellness initiative and still generate positive ROI.

When calculating the potential savings and intervention costs, we only projected savings for the proportion of the prioritized population for which we assume enrollment was successful and the intervention was effective. We assumed full intervention costs are applied to all insureds under age 90 within the prioritized population who do not opt out and do not enter a facility. This reflects the actual cost structure of the Care Concierge program, while also recognizing that savings cannot be generated if enrollment is not successful or if the intervention program is not effective.

### PROGRAM TIMING

We assumed the simulated pilot was conducted over 12 months and reflected costs and incurred savings over that period. Savings were estimated based on the present value impact of interventions over the life of each claim, but only for claims incurred within the 12 months included in the out-of-time holdout sample. Policy persistency was assumed to be 100% and all transitions in claim status were assumed to occur at midyear.

It is likely that improvements in wellness and education that occur as part of an intervention program could have continued impacts on future incurred claims once a pilot is complete. Therefore, as this analysis is based on a 12-month period, additional savings and larger ROI may be achievable if analyzed over a longer time horizon. This effect has been observed in similar LTC wellness studies.

## Savings assumptions

Savings were estimated due to three different intervention outcomes:

1. Prevented claims
2. Delayed home health care claims
3. Facility claims shifted to home care prior to transitioning to a facility

Additional detail regarding each of these outcomes is provided below. In addition to any dampening included in the assumptions described below, we applied an additional aggregate savings dampening factor to all savings assumptions. This factor varies by attained age and represents the effectiveness of any intervention (i.e., the likelihood that an intervention succeeds and/or the percentage of the population for which the intervention is successful). This effectiveness factor is assumed to be constant for ages under 81, grading to 0% at attained ages 90 and above. This reduction by attained age reflects our conservative expectation that interventions applied to older insureds may not result in savings. We increase the maximum intervention effectiveness factor in less pessimistic assumption scenarios to reflect a higher likelihood of successful intervention.

### PREVENTABLE CLAIMS

Preventable claims were identified based on diagnosis information included in the claim data. Claim diagnoses associated with injuries or due to falls were flagged as potentially preventable. Based on the claim data for insureds under age 90, approximately 10% of home health care claims and 15% of facility claims within the prioritized population during the holdout period were due to preventable causes. To reflect that not all accidents are preventable, we assumed only 25% of the claims with preventable diagnoses could be prevented as part of any intervention. The impact of preventing these claims was calculated based on the actual incurred claim dollars for identified preventable claims. After adjusting to reflect successful enrollment and applying the aggregate savings dampening factor described above, this calculation yields 0.5% of claims under age 90 weighted by count within the prioritized population (0.3% of claims under age 90 weighted by count in the total population) that are prevented in the conservative scenario.

After removing the portion of claims that were assumed to be prevented, additional savings impacts were calculated for delayed or situs-shifted claims.

### DELAYED CLAIMS

We estimated the impact of delayed home health care claims by assuming an average delay of six months and a 3.5% discount rate. After adjusting with the aggregate dampening factor, this effectively assumes an average delay of approximately two months across all home care claims in the subpopulation where enrollment was assumed to be successful. Note that using the 3.5% statutory valuation interest rate is likely conservative as many carriers earn higher yields on their assets.

### SHIFTED CLAIMS

We estimated the impact of shifting facility claims to home health care by calculating a claim reserve at incurral based on the Milliman 2020 Long-Term Care Guidelines continuance rates, a 3.5% discount rate, an average length of stay of 30 months, $4,500 per month home care costs, and $8,500 per month facility costs (based on nationwide median costs from the 2020 Genworth Cost of Care Survey).[3] We assumed claims would shift to home care for the first six months and then revert back to their original facility situs (assisted living or skilled nursing). The facility continuance rates were used for the life of the claim in all scenarios and the savings were weighted based on the actual distribution of facility claims within the claim data. After adjusting with the aggregate savings dampening factor, the impact is similar to a shift in situs of approximately two months on average across all facility claims in the subpopulation where enrollment was assumed to be successful.

Some payers may be concerned that improvements in health and the substitution of home care services for facility services early in the claim may also result in overall lengthening of claims, on average. To test the scenario, we modeled increases in facility length of stay, in addition to the shift to home health care at the beginning of the claim. Our analysis indicates that, under the conservative scenario, positive ROI is achievable even when total average length of stay increases by 10% (i.e., from 30 months to 33 months). Under less pessimistic scenarios, positive ROI is achievable with a 20% increase in total length of stay (i.e., from 30 months to 36 months). It is possible that positive ROI is achievable with even larger extensions of the average length of stay, as it is likely that decreases in utilization could also be realized if insureds are healthier overall.

Our conservative scenario assumes estimated incurred claim savings over the first 12 months of 1.0% as a percentage of total incurred claims. We expect that larger savings are achievable as part of a real-world pilot. Additionally, note that this does not capture any impacts of wellness interventions on long-term incurred claim experience. This is an area for further study once a carrier has implemented interventions and multiple years of experience are available for analysis.

## Cost assumptions

Cost assumptions include amounts for Milliman LARA analysis and fees, along with interventions by The Helper Bees. We did not assume any additional direct or indirect costs for payers (e.g., compensation for internal staff involved in wellness initiatives). Intervention costs include per member per month (PMPM) fees, along with costs associated with mailers and outreach. In our conservative assumption scenario, intervention costs were increased from current levels by 25%. We assumed full intervention costs for insureds under age 90 and we assumed insureds age 90 and older received reduced costs reflecting an education-only intervention program.

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[3] Genworth. Cost of Care Survey. Retrieved December 10, 2021, from https://www.genworth.com/aging-and-you/finances/cost-of-care.html.