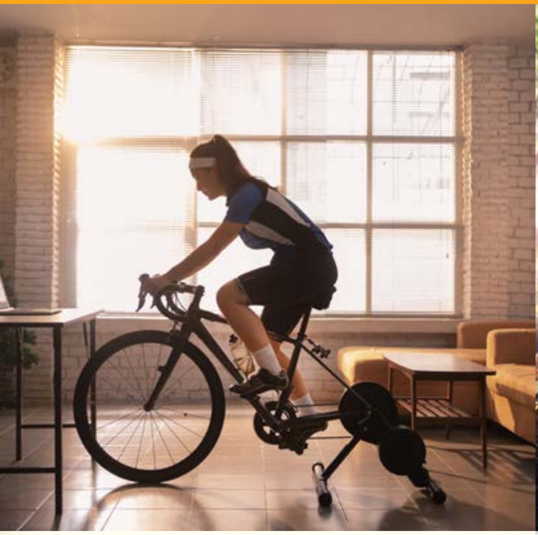
LIFE UNDERWRITING

# Personal Activity Intelligence (PAI) and Cardiorespiratory Fitness – Validated for Mortality Risk Assessment




*Gen Re Study of PAI Score*

Can activity algorithms be used to assess and predict mortality risk in Life insurance underwriting?

Gen Re's research in this area evaluates the metrics and usefulness of certain tools to effectively discriminate mortality risk in an insurance setting.

To learn more about our study and PAI Health metrics and software solutions, **contact your Gen Re account executive**.

To learn more about PAI Health, visit **paihealth.com**.

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# Personal Activity Intelligence (PAI) and Cardiorespiratory Fitness Validated for Mortality Risk Assessment

## OVERVIEW

### Physical Activity

Regular physical activity has many benefits, including lowering the risk of cardiovascular disease mortality and all-cause mortality, as well as hypertension, type 2 diabetes, adverse lipid profiles, cancers (including breast, colon, lung), dementia, anxiety, and depression.[1]

Physical activity of sufficient intensity, duration and frequency improves cardiorespiratory fitness (CRF), which is recommended as a clinical vital sign by the American Heart Association. Increasing evidence shows that CRF is a potentially stronger predictor of mortality than established risk factors such as smoking, hypertension, and high cholesterol.

Kodama et al. (2009) performed a systematic review and meta-analysis to define the quantitative relationships between CRF and coronary heart disease (CHD) events, cardiovascular disease (CVD) events, or all-cause mortality in healthy men and women. Compared with participants with high CRF, those with low CRF had 70% increase in relative risk (RR) for all-cause mortality and 56% increase in risk for CHD/CVD events.

### PAI Health

PAI Health is a health software company with expertise in biometric sensing and algorithm development.

PAI Health's proprietary metric PAI (Personal Activity Intelligence) guides people on exactly how much activity will improve or maintain their CRF and reduce their mortality risk. Published research has shown that maintaining a PAI Score of 100 or more is associated with significant CVD and all-cause mortality risk reduction across all cohorts – including across various ages, sex, geographies, and health conditions.

PAI Health

PAI interprets the heart health impact from all physical activity based on the individual's heart rate data collected from common wearable devices along with personal profile data. PAI can also estimate a user's CRF, measured as Fitness Age and VO2 max, utilizing this same data. The PAI algorithms were derived from health studies involving 45,000 people over 25 years,[2] and they have been further validated across broader populations of over 730,000 people, with over a million person-years of data.[3]

In the study, we considered whether physical activity and cardiorespiratory fitness could play a role in risk assessment of insurance applicants.


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*PAI Health app image used with permission from PAI Health.*

# METHODS

## Study Population

We obtained data from the U.S. National Health and Nutrition Examination Survey (NHANES) cycles conducted from 1999-2014 with mortality experience observed through 2015.[4] To reflect consumers of insurance, we set inclusion criteria of ages 20-80 and household income to poverty level ratio (PIR) ≥1. The study sample included 25,014 lives and 2,080 deaths, comprising 208,428 person-years of exposure.

**Figure 1 – Number of Lives and Deaths in the Original Dataset and the Data Used in the Study**

**Original NHANES Dataset (1999 to 2014, Age 20+)**

43,793 lives and 6,241 deaths

**18,779 lives and 4,161 deaths excluded by the following steps**

- 3,454 lives and 2,227 deaths with entry age >=80, no specific age for this group
- 76 lives and 4 deaths with missing mortality status or zero follow-up month
- 4,013 lives and 672 deaths with missing smoking status
- 1,673 lives and 265 death with missing variables for PAI Score estimation
- 9,224 lives and 954 deaths with missing PIR or PIR <1
- 339 lives and 39 deaths with BMI <18.5

**Dataset used in the study**

25,014 lives and 2,080 Deaths
(208,428 exposure years)

## CRF and PAI Score Estimation

The NHANES protocol for these cycles contains the elements that PAI Health used to estimate both CRF (eCRF) in three categories and PAI Score in points. These elements are age, sex, weight, height, resting heart rate and a diary of physical activity. To avoid influencing the results, PAI Heath was not given information about the source of the data or the mortality status of the participants.

## Life Insurance Underwriting Simulation

We simulated simple life insurance underwriting of the study population. To construct the aggregate standard risk population, we applied Gen Re's SOURCE-Life underwriting manual to more than 20 clinical laboratory tests typically found in insurance labs. We then applied build, personal history and family history to further stratify the standard population into two non-smoker risk classes and two smoker risk classes, using representative criteria found in the "Report of the SOA Underwriting Criteria Team."[5]

## Summary Statistics

### Table 1 – Study Population

| | Female | Male |
|---|---|---|
| **Number of participants** | 12,521 | 12,493 |
| **Follow-up years, mean** | 8.9 | 8.6 |
| **Age, mean** | 47.3 | 48.3 |
| **BMI, mean** | 29.3 | 28.8 |
| **Smoking Status, N (%)** | | |
| Non-smoking | 10,425 (83) | 9,022 (72) |
| Smoking | 2,096 (17) | 3,471 (28) |
| **Simulated Underwriting Class, N (%)** | | |
| Preferred | 2,645 (21) | 2,999 (24) |
| Residual | 7,029 (56) | 6,528 (52) |
| Substandard | 2,847 (23) | 2,966 (24) |
| **Estimated PAI Score, N (%)** | | |
| High | 3,543 (28) | 4,099 (33) |
| Medium | 3,406 (27) | 3,260 (26) |
| Low | 5,572 (45) | 5,134 (41) |
| **Estimated CRF, N (%)** | | |
| High | 4,135 (33) | 3,711 (30) |
| Medium | 4,272 (34) | 4,335 (35) |
| Low | 4,114 (33) | 4,447 (36) |

# ANALYSIS

To evaluate the efficacy of PAI Score and eCRF to enhance traditional underwriting, we performed both an actuarial actual-to-expected (A/E) mortality analysis and generalized linear modeling (GLM) on the study dataset.

For the basis for expected mortality, the 2015 Valuation Basic Table (VBT) Uni-Smoke Select & Ultimate ALB Tables were used. We chose an 80% confidence interval for the Poisson distribution as statistically significant at a level that is relevant to the mortality assessment and the business use.

Under the GLM, the Poisson distribution was chosen. The full dataset was split randomly into two parts: 70% as the training set to develop the model and 30% as the testing set to validate the model's performance.

# RESULTS

## Actual to Expected Analysis – eCRF

eCRF, as determined using the PAI Health algorithm, effectively differentiates mortality in non-smokers, as shown in Figure 2. Mortality is inversely correlated with eCRF, with low eCRF showing a statistically significant higher mortality than high eCRF by around 50% for non-smokers. The A/E analysis emphasizes the non-smoker groups. The smoker group was too small for meaningful conclusions.

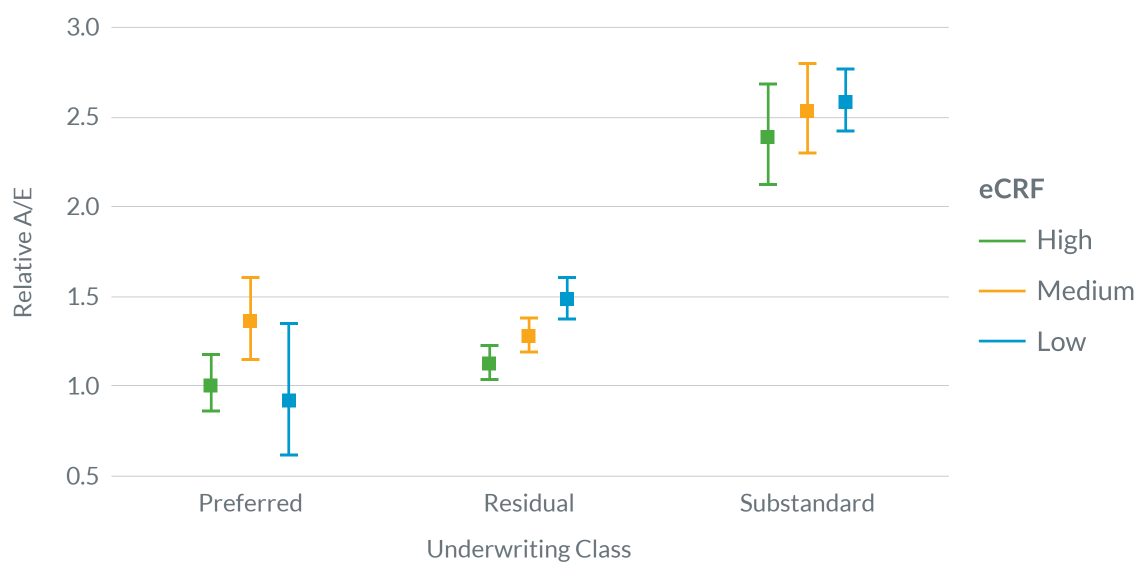
### Figure 2 – Relative Mortality A/E for Non-Smokers, by eCRF

*Reference level = Non-Smoker with High eCRF*


Figure 3 shows that eCRF stratifies risk effectively in addition to the preferred underwriting protocol. In the residual standard non-smoker group, those with high eCRF exhibit a relative mortality ratio of 112%, approximately equivalent to the overall preferred class (111% with the reference level as non-smoker with high eCRF in the Preferred class).

### Figure 3 – Relative Mortality A/E for Non-Smokers, by Underwriting Class and eCRF

*Reference level = Non-Smoker with High eCRF and Preferred Class*

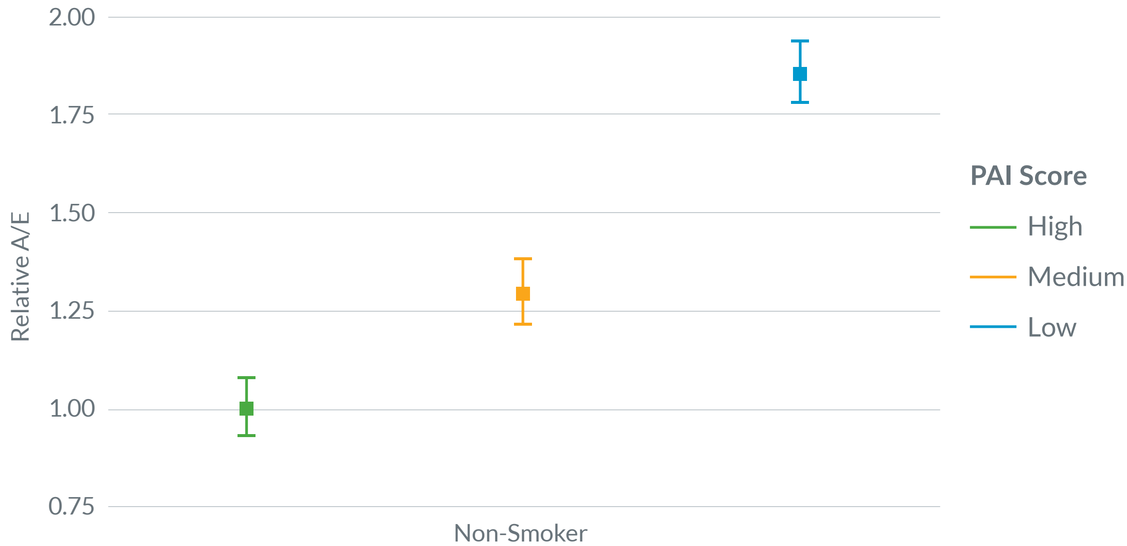


## Actual to Expected Analysis – PAI Score

We performed a similar analysis with stratification of PAI Score in three groups (Low, Medium and High). For non-smokers, PAI Score exhibited potentially greater power to differentiate mortality (Figure 4). The ratios of A/E in the least active group (Low) to the most active (High) were 185%. Differences between all three groups were statistically significant.

### Figure 4 – Relative Mortality A/E for Non-Smokers, by PAI Score

*Reference level = Non-Smoker with High PAI Score*




PAI Score performed as well or better than eCRF to differentiate within the underwriting risk class (Figure 5). The most active group among the residual standard class experienced a relative mortality ratio of 103%, which is 17% better than the overall mortality ratio of the preferred class (123% with the reference level as non-smoker with high PAI Score in Preferred class).

### Figure 5 – Relative Mortality A/E for Non-Smokers, by Underwriting Class and PAI Score

*Reference level = Non-Smoker with High PAI Score and Preferred Class*

## Generalized Linear Modeling (GLM)

We assessed the additional mortality predictive power of PAI Health metrics by building GLMs with and without PAI Score as a predictor. The table below shows the variables used in the two models and the area under the curve (AUC) for model comparison purpose.

### Table 2 – Variables and AUC in GLM

| Variables | Model 1 | Model 2* |
|---|---|---|
| Gender | ✔ | ✔ |
| Attained Age | ✔ | ✔ |
| Calendar Year | ✔ | ✔ |
| Duration | ✔ | ✔ |
| Smoking Status | ✔ | ✔ |
| Underwriting Class | ✔ | ✔ |
| PAI Score | | ✔ |
| **AUC** | **0.83** | **0.84** |

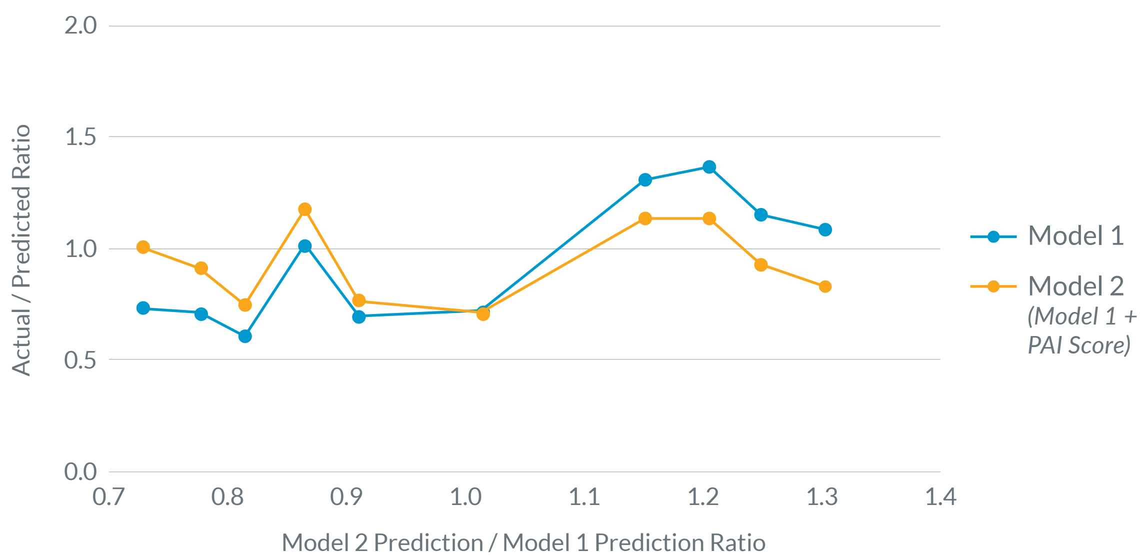
**Model 2 is Model 1 + PAI Score*

The GLM results indicate PAI Score is a significant predictor of mortality. Model 2 with PAI Score has a small improvement in AUC compared to Model 1 without PAI Score. We created a double lift chart[i] to compare the outcomes from the two models on the testing set. Figure 6 shows the ratio of actual to predicted by the agreement of predictions from the two models:

> The models' predictions can diverge by as much as 30%.

> When the predictions are different, Model 2 with PAI Score has better predictive power in most cases, i.e., the actual over predicted ratios are closer to 1.

### Figure 6 – Double Lift Chart to Compare the Outcomes




The A/E analysis shows eCRF discriminates the risks in the residual standard group effectively (Figure 3); however, eCRF was not included in the final GLM model due to the possible multicollinearity of the dataset. According to the correlation statistics, eCRF has medium level association with both Underwriting Class and PAI Score. This multicollinearity issue may be overcome when more data is available.

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[i] *The double lift chart was created by sorting the test data by ratio of Model 2 prediction to Model 1 prediction, and subdividing sorted data into quantiles with equal exposure, then calculating the ratio of actual to model prediction of each model in each quantile.*

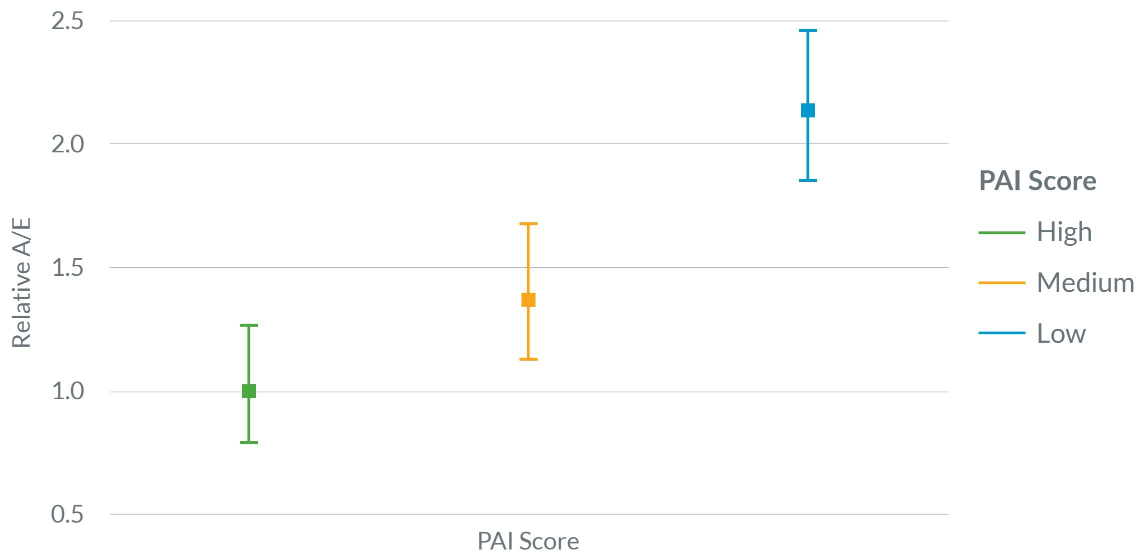
## PAI Score vs. Step Count

One NHANES survey provides counts of steps of participants for one week. In this subset, where we had both PAI Score and step count, we compared mortality experience. Figures 7 and 8 show PAI Score can differentiate among the non-smoking risks better than step count. Step count did not differentiate between high and intermediate activity. Both measurements distinguish the least active cohort well. The correlation between PAI Score and step count is small, according to the correlation analysis.

This result, which may appear paradoxical, is due to a fundamental difference between PAI Score and step count. First, PAI Score measures activity by increase in heart rate and therefore captures all forms of activity, including those that produce minimal step counts, such as biking or swimming. Second, PAI Score captures two dimensions of the exercise data in a combined score: intensity and amount of exercise. By contrast, step count only captures one: the amount.

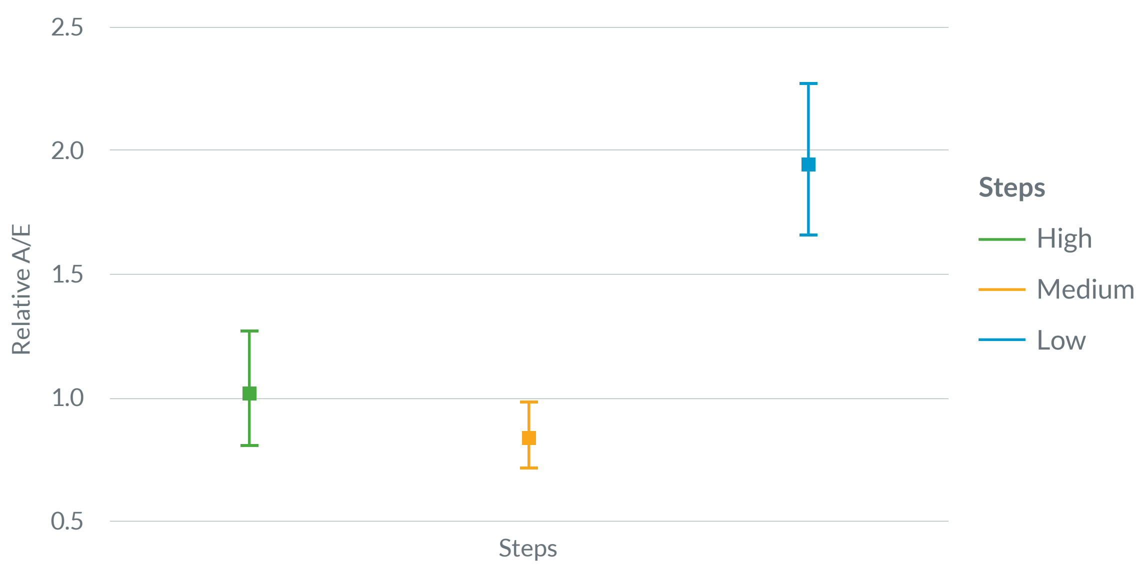
### Figure 7 – Relative Mortality A/E for Non-Smokers, by PAI Score

*Reference level = Non-Smoker with High PAI Score*




### Figure 8 – Relative Mortality A/E for Non-Smokers, by Daily Steps

*Reference level = Non-Smoker with High Daily Steps*



# CONCLUSIONS

Application of PAI Health assessment of eCRF and PAI Score confirms that both measures effectively discriminate mortality risk in the NHANES population.

Our research validated four key features that are critical for using PAI Health metrics in an insurance setting:

> Data from the general population for those who use a fitness device with heart rate monitoring allows determination of eCRF and PAI Score.

> PAI Health metrics correlate with mortality.

> PAI Health metrics assess mortality risk independently of traditional underwriting factors.

> One-time assessment of eCRF or PAI Score predicts mortality risk for many years.

Contact your Gen Re representative to learn more about using PAI Health metrics and software solutions.

## Endnotes

1. Piercy KL, Troiano RP, Ballard RM, et al. The physical activity guidelines for Americans. JAMA. 2018;320(19):2020-2028.

2. https://www.sciencedirect.com/science/article/pii/S0002934316310695.

3. https://www.sciencedirect.com/science/article/pii/S0033062020301134#ab0005,
https://www.sciencedirect.com/science/article/abs/pii/S0033062018301890,
https://www.mayoclinicproceedings.org/article/S0025-6196(18)30321-5/abstractm,
https://academic.oup.com/ije/article/42/4/968/655743,
https://www.ntnu.edu/cerg/vo2max.

4. The National Health and Nutrition Examination Survey (NHANES) is a program of studies designed to assess the health and nutritional status of adults and children in the U.S. NCHS is part of the Centers for Disease Control and Prevention (CDC).

5. https://www.soa.org/globalassets/assets/files/research/exp-study/research-under-criteria-report.pdf.

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