



# Closing the gap

How wearable data reduces mortality  
slippage in accelerated underwriting

Two of the largest sources of mortality slippage in accelerated underwriting are missing fluid information and smoker misrepresentation. In collaboration with Klarity,<sup>1</sup> WTW tested whether using the Klarity predictive model's wearable-based risk score — analyzed in our July 2025 paper, “Reclassifying Mortality Risk”<sup>2</sup> — can narrow that gap without the protective value of fluids.

WTW's July 2025 paper centered on our analysis of Klarity's mortality risk predictive model and the powerful predictive value of leveraging activity- and inactivity-based data in the risk selection process. The Klarity model classifies individual risk using a Z-score, which reflects how much a person's predicted risk deviates from the average for their age and gender group.

Our initial study focused on the additive value of activity-based data and the model risk score to underwriting, where certain fluid variables, such as cholesterol, were also included in the model scoring.

Given the prevalence of more accelerated underwriting (AUW) programs in the U.S., where fluid variables from insurance labs and physical measurements are often

waived. In this analysis, we tested if the Klarity model risk score when no fluids were included could be leveraged to reduce the mortality slippage that results from missing fluid information and smoker misrepresentation, which continues to be a challenge for most AUW programs.

WTW found inclusion of alternative activity-based data, is additive to the risk selection process. In this study, we found adding the Klarity model's risk score, even when fluid or insurance lab data are included, improves the ability to better segment the risks within a targeted risk class. Thus, we believe the inclusion of the Klarity risk score can likely reduce the mortality slippage observed in AUW due to certain misrepresentation.

**In our July 2025 paper, we identified the following findings:**

- Lifestyle factors such as daily activity duration, step count, sleep and inactive time strongly correlate with mortality
- The Klarity model identifies a clear gradation of mortality risk, even flagging a small subset of traditionally insurable risks that exhibit notably higher mortality risks and may be rated or uninsurable
- Many “best” class lives (as defined by traditional underwriting) showed higher mortality risk, and many “standard” or residual lives reflected Z-scores aligned with lower risk (i.e., better mortality). Therefore, reclassifying risks aligned with Z-scores enables a more accurate classification of the mortality spread within each class
- The Klarity model can better classify risks and reduce the overlap inherent in today's risk classification systems



<sup>1</sup> Klarity is a U.K.-based predictive analytics company that provides preventive health solutions. Its proprietary mortality and morbidity risk prediction models leverage advanced data sources such as wearables, electronic health records and blood biomarkers.

<sup>2</sup> <https://edge.sitecorecloud.io/willistower8735-wtw7458-prode832-66e2/media/project/wtw-sites/wtwco/insights/2025/08/reclassifying-mortality-risk.pdf>

# Our approach

For the study to analyze the mortality slippage, we organized predictive variables into three cohorts: demographic variables, wearable variables and fluids variables. The demographic variables include the insureds' age, sex, weight, history of diseases and other information that are commonly included in a simplified underwriting questionnaire. The activity variables include average daily step count, average nightly hours of sleep, heart rate, activity time and inactivity time. The fluids variables include a list of fluids and markers commonly obtained with traditional insurance blood and urine/home office specimen (HOS) testing, such as cotinine (we requested Klarity use the U.K. Biobank<sup>3</sup> smoker data as a proxy for a cotinine test), cholesterol, proteins and blood pressure (which would be obtained along with the fluid collection).

| Demographics                                                                                                                                                                                           | Wearables                                                                                                                                                     | Fluids                                                                                                                                                                                                                |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <ul style="list-style-type: none"><li>• Age</li><li>• Sex</li><li>• Body mass index</li><li>• History of disease</li><li>• Family history of disease</li><li>• Statins</li><li>• Alcohol use</li></ul> | <ul style="list-style-type: none"><li>• Steps Count</li><li>• Activity Time</li><li>• Inactivity Time</li><li>• Sleep Duration</li><li>• Heart Rate</li></ul> | <ul style="list-style-type: none"><li>• Lipids</li><li>• Liver function</li><li>• Renal function</li><li>• Metabolic</li><li>• Nicotine exposure (cotinine)</li><li>• Systolic and diastolic blood pressure</li></ul> |

Our initial study leveraged the U.S. National Health and Nutrition Examination Survey (NHANES) data set,<sup>4</sup> in addition to the U.K. Biobank data. The NHANES data does not include as robust a range of insurance lab or activity-based data as the U.K. Biobank data, which is rich in activity data and includes comprehensive blood biomarker panels. To conduct a direct head-to-head comparison of wearable signals versus fluid biomarkers, Klarity leveraged only the U.K. Biobank data for the analysis. This provided the ability to include objective accelerometer data and a full panel of blood biomarkers for the same individuals, enabling a like-for-like comparison within a single cohort, using the same outcome and evaluation methodology.

To better mimic the characteristics of an insured applicant pool of individuals, Klarity filtered the Biobank data on the age at the beginning of the study to be between 40 and 65 and an Index of Multiple Deprivation set to exclude the bottom 20% in socioeconomic status.

We fit four models to demonstrate the improvements gained from including additional predictors. The first model was a demographic-only model, which may be similar to simplified, questionnaire-only underwriting coupled with instantly available information such as prescription histories. The second model added wearable data to the demographic model, and the third model used demographic, wearable, and typical insurance blood and HOS panel data plus diastolic and systolic blood pressure levels.

Klarity ran the Biobank data through each of the four models to compare each model's predictive performance using AUC.<sup>5</sup> A higher AUC represents an improvement in the predictive performance of the model being measured.

| Model                             | AUC   |
|-----------------------------------|-------|
| Demographics only                 | .7686 |
| Demographics + Wearables          | .7896 |
| Demographics + Fluids             | .7928 |
| Demographics + Wearables + Fluids | .7994 |

AUC scores were highest when fluids were included. The use of additional wearable data improved the AUC, even when fluids were also collected. While using activity-based data and the Klarity model shows promise toward improving the risk prediction, we note that further testing with more data (specifically actual insured applicant data) is needed to ensure that these differences are statistically significant.

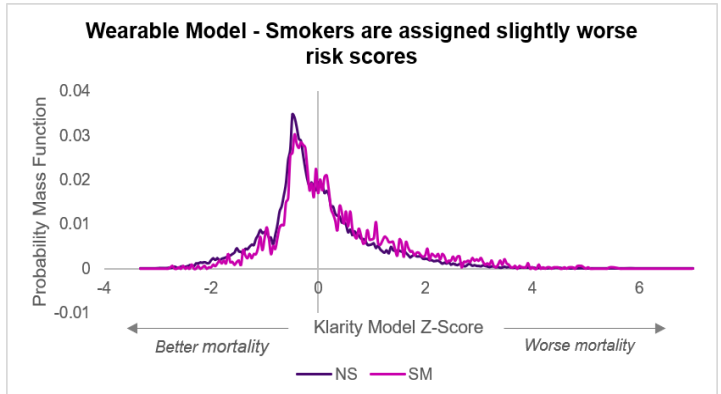
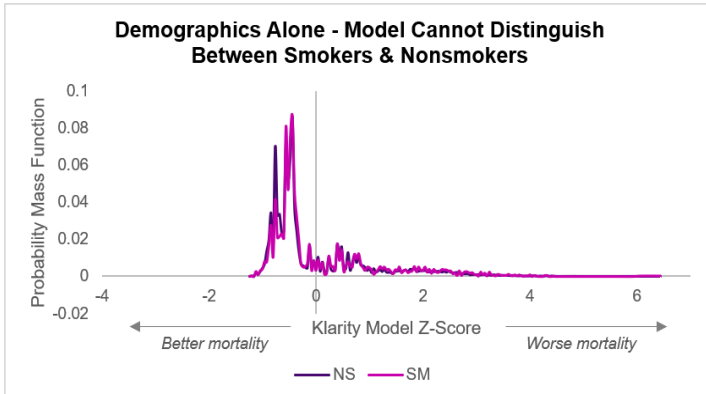
We then analyzed how well the Klarity model, through its distribution of Z-scores, could distinguish smoker risks, absent fluid data. The following figures demonstrate the distribution of Z-scores.

<sup>3</sup> A prospective longitudinal study of de-identified individuals drawn from the U.K. population representative of the U.K. general population. This data set contains 502,369 lives and 37,897 deaths recorded during the 10-year follow-up period from a population spanning enrollment mainly of ages 40 to 70 and observed an average period of 13.5 years to track health outcomes, including mortality. Information about U.K. Biobank can be found at [www.ukbiobank.ac.uk/enable-your-research/about-our-data](http://www.ukbiobank.ac.uk/enable-your-research/about-our-data).

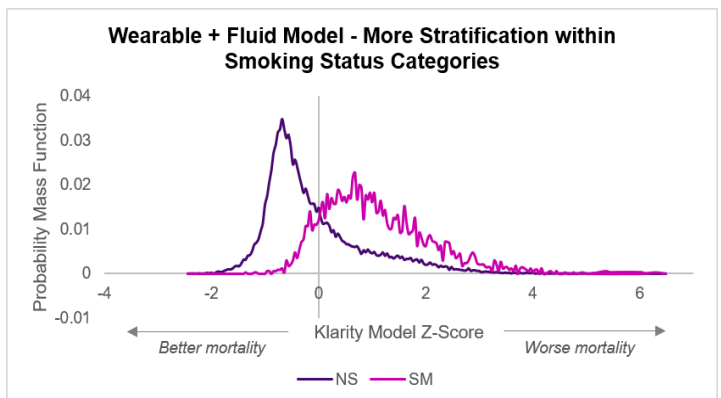
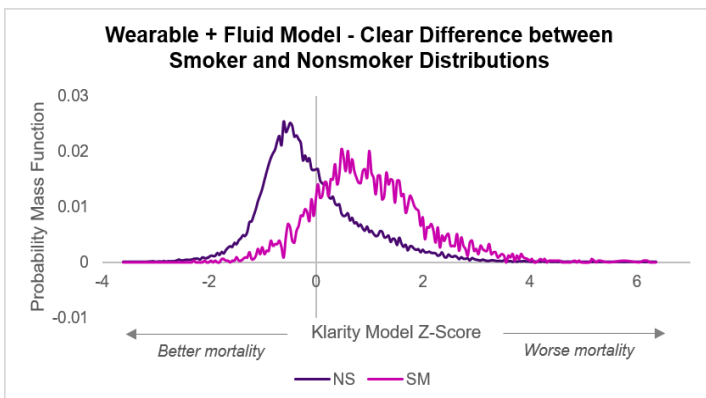
<sup>4</sup> A cross-sectional survey run by the National Center for Health Statistics, part of the Centers for Disease Control and Prevention (CDC). NHANES has run continuously since 1999 and includes approximately 5,000 participants each year, combining surveys with physical examinations. Information about NHANES can be found at [www.cdc.gov/nchs/nhanes/about/index.html](http://www.cdc.gov/nchs/nhanes/about/index.html).

<sup>5</sup> AUC measures a model's ability to distinguish between two outcomes (in this case, death vs. survival over the 10-year follow up period). It represents the probability that the model assigns a higher predicted risk to a randomly selected positive case than to a randomly selected negative case. Values range from 0.5 (no predictive power) to 1.0 (perfect discrimination).

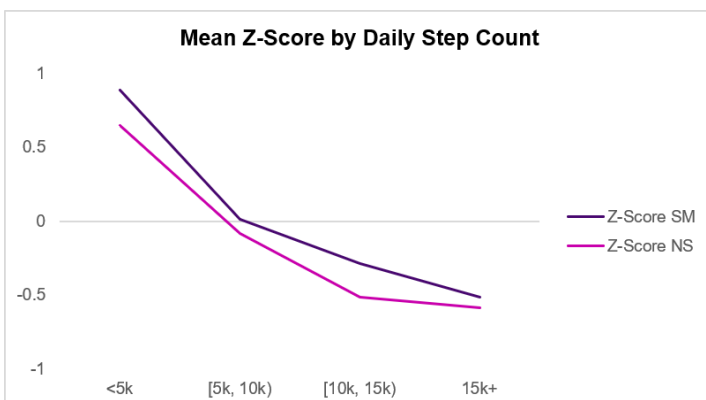
Neither demographic data alone nor combined with the additional predictors are effective at distinguishing smoker risks from nonsmoker risks, though the Klarity model does assign slightly higher risk scores (i.e. worse mortality) to smoker risks.



Inclusion of the protective value of fluids more clearly distinguishes between nonsmoker and smoker risks, though inclusion of activity-based data improves the overall results, specifically in the stratification of nonsmoker mortality.



Inclusion of the activity-based data, such as step count, does identify healthier from less healthy individuals, whether smoker or nonsmoker risks.



## Key Findings

We have several key findings from this analysis:

- The addition of wearable-based data improved both the demographic-only and demographic-plus-fluids models, so its inclusion is beneficial with an increase in predictive performance. The addition of wearable data to information typically available for AUW and traditional UW provides improved risk selection.
- The Klarity model can distinguish and select healthier smokers from those less healthy; however, the model is not able, without additional fluid data or reliable self-admitted smoking history, to distinguish clearly between smokers and nonsmokers. Smoking status is most accurately captured by a cotinine test.
- Given that automated underwriting programs already do not have definitive tobacco-use information, the ability to narrow the impact of smoker misrepresentation by removing the less healthy smokers remains additive to the risk selection process.
- The Klarity model can be used to improve the overlap of risk classes; coupled with additional tools such as Rx (which may have tobacco information, clinical lab data and targeted electronic health record information), the use of activity-based data provides another lens to better classify and/or triage risk classes.

## Limitations

While we adjusted data where possible, our research has certain limitations. We continue to be optimistic that these limitations can be reduced with the use of U.S.-based insurance data. The amount of smoker data within the Biobank data is fairly limited, with about 3,000 lives and 350 deaths. The Biobank collects smoker data via self-reporting rather than a cotinine test. We note that, based on the nature of the study, participants have little incentive to misrepresent their smoking habits. Therefore, we believe the self-admitted history within the Biobank data set is a reasonable proxy for a cotinine test. As noted, these data were tested on U.K. population data. It would be beneficial to perform these tests on U.S. insured data, which would allow us to measure any drop in performance as well as to tailor the model to U.S.-specific risks. Finally, unlike our prior study, we have not baselined the predictions against a base mortality table.

## Next steps

Partnering with a U.S. insurer will offer further insight into how the Klarity model can create value in underwriting. While we have adjusted the data to be representative of an insurance applicant pool, additional testing on insured applications is needed. Further, throughout our testing, Klarity has shown the ability to hone its model on a specific data source to improve predictions. As more U.S. companies participate, Klarity's model will continue to become better at predicting these risks.

We are also planning a future paper to analyze the cost-benefit assessment of Klarity's model, using our hypothetical block of business. This will show the impact of improved risk categorization, improving the mortality distribution for each risk classification, reducing right-tail risks within the classes and reducing overlap among the risk classes.

## Conclusion

Activity- and inactivity-based data, delivered through the Klarity mortality risk model, offers a compelling new lens for risk selection. The model's signals are predictive and can help align underwriting outcomes more closely with pricing expectations.

Traditional insurance labs remain the strongest safeguard against key misrepresentation risks, particularly smoking. But adding activity- and inactivity-based data creates another layer of protection — and a sharper view of risk segmentation.

Smoker misrepresentation remains a major source of AUW mortality slippage. Klarity Z-scores show promise in identifying healthier smokers and reducing that slippage by capturing cardiovascular indicators such as pulse, blood pressure, heart rate and sleep.



## Appendix 1: Fluid biomarkers

In this study, 16 blood biomarkers were used, spanning four major physiological systems:

### Lipid profile: Cardiovascular risk markers

**Total cholesterol:** Overall circulating cholesterol level; elevated total cholesterol is a primary risk factor for atherosclerosis and cardiovascular mortality.

**HDL (high-density lipoprotein):** The “protective” cholesterol; higher HDL is associated with reduced cardiovascular risk by facilitating cholesterol transport from arteries to the liver.

**Total cholesterol: HDL ratio:** A composite cardiovascular risk marker; higher ratios indicate greater atherogenic risk and are often preferred over absolute cholesterol values alone.

**LDL:HDL ratio:** The balance of “bad” to “good” cholesterol; a higher ratio is associated with increased plaque formation and coronary heart disease risk.

**Total triglycerides:** Blood fat levels reflecting energy storage and lipid metabolism; elevated triglycerides are associated with metabolic syndrome, pancreatitis and cardiovascular risk.

### Liver function markers: Hepatic health and systemic inflammation

**Alkaline phosphatase (ALP):** An enzyme elevated in liver and bone disease; elevated ALP is associated with biliary obstruction, liver damage and increased mortality in population studies.

**Alanine aminotransferase (ALT):** A liver-specific enzyme; elevated ALT indicates hepatocellular damage from conditions such as fatty liver disease, hepatitis and alcohol-related liver injury.

**Gamma-glutamyl transferase (GGT):** Sensitive marker of liver stress and alcohol intake; elevated GGT is associated with liver disease, metabolic syndrome and cardiovascular mortality.

**Aspartate aminotransferase (AST):** An enzyme elevated in liver cell damage and myocardial injury; the AST:ALT ratio is clinically informative for distinguishing types of liver disease.

**Total bilirubin:** A breakdown product of haemoglobin; moderately elevated bilirubin may be associated with reduced oxidative stress, while markedly elevated levels indicate liver or haematological pathology.

**Albumin:** The most abundant plasma protein; low albumin indicates poor nutritional status, chronic liver disease, or systemic inflammation and is a strong predictor of all-cause mortality.

**Globulin:** A broad marker of immune and inflammatory activity; elevated globulin is associated with chronic infection, inflammatory conditions and haematological malignancies.

**Total protein:** The sum of albumin and globulin; reflects overall nutritional status, hepatic synthetic function and immune activity.

### Renal function markers: Kidney health

**Urea:** A waste product of protein metabolism excreted by the kidneys; elevated urea indicates reduced kidney filtration capacity and is associated with increased mortality in general population studies.

**Creatinine:** A muscle metabolism by-product cleared by the kidneys; elevated creatinine is the primary marker of impaired renal function and is used to estimate glomerular filtration rate.

### Metabolic marker: Glucose regulation

**Glucose:** Fasting blood glucose level; elevated glucose indicates impaired insulin sensitivity or diabetes, which carries substantially elevated cardiovascular and all-cause mortality risk.

These 16 biomarkers collectively provide a detailed snapshot of the individual's cardiovascular risk profile, liver and kidney function, metabolic status, and inflammatory burden, but only at the moment of blood collection. Repeated measurement is required to track change over time.

In addition, when the predictive value measure included fluids, we also included diastolic and systolic blood pressure limits, presuming that, if fluids are collected, actual blood pressure limits, rather than total blood pressure level available from a wearable device, would be available.



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