The Hilltop Pre- Models

In Brief

December 2023

1. Intended Use

The Hilltop Pre- Models are risk prediction models developed by The Hilltop Institute at UMBC that use a variety of risk factors derived from Medicare claims data to estimate the event risk that a given patient incurs a given outcome in the near future. As of November 2022, there are three such prediction models in production for the Maryland Primary Care Program (MDPCP) population: the Hilltop Pre-AH Model™, which generates the "Avoidable Hospitalizations (Pre-AH)" scores; the Hilltop Pre-DC Model™, which generates the "Severe Diabetes Complications (Pre-DC)" scores; and the Hilltop Pre-HE Model™, which generates the "Hospice Eligibility and Advanced Care Planning (Pre-HE)" scores. These risk scores are displayed in the MDPCP Prediction Tools area on Chesapeake Regional Information System for our Patients (CRISP).

These risk scores are intended to help MDPCP-participating practices identify beneficiaries who have a high risk of incurring an avoidable hospitalization or emergency department (ED) event, a high risk of incurring a hospital event due to severe diabetes complications, or a high risk of eligibility for hospice. Using this information in conjunction with clinical judgement, providers can make informed decisions about allocating scarce care coordination resources, directing these resources to the individuals who will benefit from them the most.

a. Differentiation from CMS HCC Risk Scores

The Hilltop Pre- Model risk scores are conceptually distinct from the Centers for Medicare & Medicaid Services (CMS) Hierarchical Condition Category (HCC) risk scores that are also presented in the CRISP MDPCP dashboard. The Hilltop Pre- Model risk scores use risk factors based on diagnoses, procedures, medications, utilization, demographics, and geographic factors to produce a practice-specific ranking of patient **risk for a given outcome in the near future**. The

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CMS HCC risk scores are based on a model that uses diagnosis codes and a limited set of demographic information from a base year in order to predict *expenditures* over the following year. There is likely to be some overlap among individuals who incur, for example, an avoidable hospitalization and individuals who experience high medical spending, but the overlap is unlikely to be complete. High medical expenditures can reflect a number of factors ranging from moderate utilization of high-cost procedures, high utilization of moderate-cost procedures, underlying morbidity, or geographic differences in treatment or referral practices.

Additionally, it is important to note that "risk" for the CMS HCC risk model refers to *actuarial* risk; this model seeks to predict average expenditures over large groups of individuals. In contrast, the Hilltop Pre- Model risk scores are designed to estimate, as closely as possible, event risk; that is, an *individual's* risk of incurring a given outcome in the following months.

Finally, there are differences in the time horizons of each risk score. CMS HCC "final risk scores are generally available 16-18 months after the close of the base year. For example, 2017 risk scores (based on 2016 diagnoses) will be available in the spring of 2018"(Center for Medicare and Medicaid Innovation, 2017, p. 26). The Hilltop Pre- Model risk scores, however, are updated monthly and use patient-level risk factor information current to the **most recently available month of Medicare claims in order to generate risk scores**. This is a strength of the Hilltop Pre-Models; these risk scores reflect the underlying patient condition with a lag of only—at most—three months.

b. Use Case Example

In order to illustrate the intended use of the Hilltop Pre- Models, we have created a hypothetical clinical vignette using the Hilltop Pre-AH Model™ risk scores for an MDPCP practice. For the sake of exposition, the patient panel consists of thirteen patients, each of whom represents ten similar patients. Table 1 on the following page displays the patient panel, along with each patient's (hypothetical) Hilltop Pre-AH Model™ risk score and CMS risk tier.

Patients in this practice are listed in descending order of risk. Based on the most recently available month of risk factors spanning diagnoses, procedures, medications, utilization, demographics, and geographic information—in conjunction with risk coefficients derived from training data—Patient 1 (or, equivalently, the ten patients represented by Patient 1) has a 75% chance of incurring an avoidable hospital event in the near future. Patient 2 is the next riskiest and has a 15% chance of incurring an avoidable hospital event. Patient 3 is the next riskiest, with a 5% chance. The distribution of risk is highly skewed: the majority of the practice's panel has less than a 1% chance of incurring an avoidable hospital event, and all but two of the patients have under a 6% event risk.

Distributing available care coordination resources equally to all 130 underlying patients would result in each patient receiving a relatively small portion of available resources. This distribution of resources may be unlikely to have a significant impact on patient outcomes: the low-risk individuals would be low-risk even without the advanced primary care intervention, and the high-risk individuals may require more resource-intensive interventions to experience improvement in outcomes.[1] The Pre-AH Model™ risk scores, used in conjunction with provider clinical guidance, can assist practices with a more efficient and impactful allocation of their care management efforts.

Table 1. Hypothetical Patient Panel

Patient Name	Pre-AH Risk Score (%)	CMS Risk Tier
Patient 1	75%	Complex[2]
Patient 2	15%	Complex
Patient 3	5%	Tier 4
Patient 4	4%	Complex
Patient 5	2%	Tier 3
Patient 6	1%	Tier 3
Patient 7	Less than 1%	Tier 2
Patient 8	Less than 1%	Tier 2
Patient 9	Less than 1%	Tier 1
Patient 10	Less than 1%	Tier 2
Patient 11	Less than 1%	Tier 1
Patient 12	Less than 1%	Tier 1
Patient 13	Less than 1%	Tier 1

c. *Reason for Risk*

As of January 11, 2020, the "Avoidable Hospitalizations (Pre-AH)" scores have included the top actionable risk factors underlying each patient's risk of incurring a future avoidable hospital event. This functionality is also available for the "Severe Diabetes Complications (Pre-DC)" scores and the "Hospice Eligibility and Advanced Care Planning (Pre-HE)" scores.

[1] Liaw et al. (2015) conclude that, based on a review of four CMS-funded demonstrations involving care management fees, "to generate savings, resource allocation cannot be homogeneous. Instead, practices must focus more intensely on those at highest risk of utilization" (p. 557). Indeed, this may (partly) explain the varying effectiveness of care management, care coordination, and intensive primary care interventions as documented in the academic literature; many patients have low underlying risk of adverse outcomes, thus obviating the need for intervention, and the few high-risk patients may require significant intervention resources. For summaries of the literature on this subject, see Edwards et al. (2017) and Baker et al. (2018).

[2] It is important to note that while the CMS risk tier is correlated with Hilltop Pre-AH Model™ risk scores, the correlation is not perfect, for two reasons. First, CMS risk tiers are based on underlying HCC score, which is conceptually distinct from the Pre-AH risk score. Second, certain groups of patients are automatically assigned to certain CMS risk tiers, which further reduces the correlation between the two measures. In particular, beneficiaries without sufficiently long clinical histories are assigned to CMS risk tier 2, while beneficiaries with "a diagnosis of dementia, substance use disorder, or severe and persistent mental illness" are assigned to the Complex tier, regardless of their HCC score (Center for Medicare & Medicaid Innovation, 2019). These individuals may, in turn, have relatively low (or high) risk of avoidable hospitalizations, meaning that an individual in, for example, the Complex CMS risk tier may have a low Pre-AH risk score. We highlight this point in Table 1 by presenting a non-monotonic relationship between Pre-AH risk score and CMS risk tier.

The intention of this update is to augment the information provided to practices in order to further facilitate patient-specific advanced primary care. For example, in addition to a risk score of 3.2% for a particular patient, care managers can drill down on a particular patient to see the factors that most contribute to the patient's risk of (for example) incurring an avoidable hospital event. While a patient may have many risk factors for a given outcome, Hilltop only displays the most predictive, intervenable risk factors in order to allow care managers to focus their attention on the most pressing patient needs.

The reasons for risk are the top actionable risk factors underlying each patient's predicted risk of incurring a given outcome (either an avoidable hospital event, a severe diabetes complication event, or eligibility for hospice). It is important to note that these risk factors are not necessarily causal; that is, just because a patient has a certain risk factor does not mean that the risk factor *causes* that patient to have increased risk of incurring a given outcome. However, these risk factors have been statistically validated as being strongly *associated* with increased risk of incurring a given outcome. Thus, they can equip providers and care managers with a useful starting point in the delivery of advanced primary care to high-risk patients.

While each of Hilltop's predictive models contain over 200 risk factors, only a subset of these is included in the pool of potential reasons for risk because of statistical interpretation and clinical utility. Most non-binary and non-count risk factors are excluded because these cannot easily be translated into reason for risk contributions for lack of a meaningful reference group. Additionally, based on the feedback from stakeholders, Hilltop excludes risk factors that are not potentially modifiable; that is, for which the effects cannot be meaningfully modified by clinical intervention (like, for example, area income). Finally, risk factors that are not positive and statistically significant are also excluded.

For each model, users can also see the relative contribution of each risk factor category (Condition, Demographic, Pharmacy, Utilization, and Environmental) in percentage terms. These are intended to provide a high-level description of the contribution of various types of risk factors that are positive and significant for an individual. The contribution for a given category is calculated as the sum of (risk factor level * coefficient) for all reasons for risk in that category, divided by the sum of (risk factor level * coefficient) for all positive, statistically significant reasons for risk. An individual's *overall* risk is a function of **all** risk factors, including those that are not included as potential reasons for risk. The category contributions, however, are only interpretable relative to the reason for risk factor pool, which is restricted to the clinically modifiable risk factors.

2. Technical Implementation

This section presents details on data sources, risk factors, methodology, and model performance.

a. Data Sources

The Hilltop Pre- Models rely largely on data from Claim and Claim Line Feed (CCLF) Medicare claims files, supplemented with various publicly available environmental data sets used to generate the environmental risk factors. These data sources are detailed below.

i. CCLF Data

The majority of the risk factors in each of the Hilltop Pre- Models are derived from CCLF Medicare Parts A, B, and D claim files. Each month, Hilltop receives Part A claims, Part A revenue centers, Part A procedure codes, Part A diagnosis codes, Part B claim lines, Part B durable medical equipment claims, Part D claims, and patient demographic information (which also includes eligibility information) from CMS. Additionally, Hilltop receives beneficiary attribution files and practice rosters each quarter.

Upon receipt of the monthly claims files, Hilltop first performs automated data validity checks in order to assess the integrity of the CCLF data files, followed by a data reduction step that subsets the claims files against the beneficiary attribution file. The resulting files retain the raw claims data that are inputs to the risk factor feature engineering process. At the time of writing, the resulting data include approximately 375,000 individuals across over 500 practices. These individuals incurred approximately 2.9 million part A claims, 56.6 million part B claim lines, and 19.8 million part D claims in the three-year period of August 2019 to July 2022.

Using SAS 9.4, Hilltop creates the model using risk factors identified in the literature review.[3] The risk factors are briefly described below and in greater detail in Appendix 1 in *Risk Score Specifications and Codebook for The Hilltop Institute's Pre- Models (Version 1)*.

ii. Social Determinants of Health (SDOH) Data Set

Social and environmental variables play an important role in health; however, many individual-level demographic and socioeconomic factors (for example, marital status) are unavailable in administrative claims data. Consequently, Hilltop developed an extensive database of area risk factors from publicly available data sources (i.e., the percentage of the population aged 15+ that is currently married) that can be linked to an individual's administrative claims using their recorded address to proxy for the unobserved individual-level variables. Other environmental risk factors (e.g., area poverty rate) are intended to capture social determinants of health—the neighborhood conditions in which people live and age that may affect health outcomes. Hilltop created two versions of these variables: one that maps to an individual's ZIP code (ZCTA) and, in October 2021, more granular versions of the variables at the census tract level.

Hilltop enhanced the granularity of the SDOH risk factors from ZCTA to census tract as part of regular improvements to the production model in October 2021. We increased the granularity of

[3] Certain risk factors identified in the literature review were not ultimately operationalizable in Phase 1 of the Hilltop Pre-AH Model™. We will incorporate additional risk factors in future iterations of the model.

the SDOH covariates because research shows that there can be substantial variability of SDOH within ZCTAs. For additional detail on data sources and methodology, see Appendix 2 in *Risk Score Specifications and Codebook for The Hilltop Institute's Pre- Models (Version 1)*.

b. Risk Factors

This section provides a brief overview of the risk factors included in the Pre- Models. For additional detail, please see Appendix 1 in *Risk Score Specifications and Codebook for The Hilltop Institute's Pre- Models (Version 1)*.

i. Literature Reviews

As a first step in the model development process, Hilltop conducted a thorough literature review to identify factors that are associated with avoidable hospital events. In the original literature review, the Hilltop team screened over 3,300 articles in both a primary and secondary literature search, ultimately selecting 211 articles for risk factor extraction. In the development of the Hilltop Pre-DC Model™, the team screened 107 articles and selected 35 articles for full-text review. In the development of the Hilltop Pre-HE Model™, the team screened 80 articles and selected 22 articles for full-text review.

Ultimately, these literature reviews yielded 204 risk factors in the Hilltop Pre-AH Model™, as well as an *additional* 18 risk factors in both the Pre-DC Model™ and the Pre-HE Model™. All 204 Pre-AH Model™ risk factors are used in the Pre-DC and Pre-HE Models *in addition to* the supplemental risk factors identified in the respective literature reviews.

ii. Part A, B, and D Risk Factors

Risk factors based on Part A claims cover information on admissions over the past 12 months; nursing home stays over the past 12 months; and certain procedures. Additionally, the Part A claims are used in order to construct both the avoidable hospital event outcome and the severe diabetes complications event outcome, as well as the diagnostic condition flags. These condition flags rely on diagnostic information from Part A and Part B claims in conjunction with Chronic Conditions Data Warehouse (CCW) coding specifications in order to generate beneficiary-level risk factors that represent underlying disease states.[4]

Risk factors based on Part B claims cover utilization of certain services (such as vaccinations, lab tests, or J-code procedures), place of service (for example, urgent care or rural health clinic), and provider specialty (for example, endocrinology or oncology). Hilltop also created risk factors to capture a beneficiary's primary care utilization and continuity of care.

Using Medicare Part D claims, Hilltop flags utilization of drugs identified in its literature review as potential risk factors for potentially avoidable hospital events. In order to capture compound

[4] Additional detail on the CCW condition flag specifications can be found here:
https://www.ccwdata.org/documents/10280/19139421/ccw-chronic-condition-algorithms.pdf,
https://www.ccwdata.org/documents/10280/19139421/ccw-chronic-condition-algorithms-reference-list.pdf

drugs, which are drugs that contain multiple active ingredients, Hilltop relies largely on text-based, “contains”-type searches of the FDA’s “National Drug Code Directory.”[5]

iii. Environmental Risk Factors

The literature reviews identified dozens of area-level risk factors that have been shown to be predictive of avoidable hospital events, severe diabetes complication events, or near-term all-cause mortality. In general, such risk factors are predictive for one of two reasons: either they proxy for individual-level risk factors that are not available in the CCLF data, or they capture area-level factors (for example, provider availability) that may impact health outcomes. As noted above, Hilltop increased the granularity of the pool of environmental risk factors from the ZCTA level to the census tract level in October 2021.

c. Modeling

Methodologically, Hilltop relies on a discrete time survival model that uses current values of procedural, diagnostic, utilization-based, pharmacy, demographic, and environmental risk factors to predict the likelihood that an individual incurs a given outcome in the *following* month. The parameter estimates generated in the model training are subsequently used to generate individual risk predictions in the scoring step. We assess the quality of our modeling using monthly concentration curves, which measure the cumulative share of all outcomes actually incurred by the riskiest (predicted) patients.

i. The Hilltop Pre-AH Model™

The outcome measure in the Hilltop Pre-AH Model™ is a 0/1 indicator variable denoting whether an individual incurred an avoidable hospitalization or ED visit in a given month. To construct this measure, Hilltop relies on technical definitions provided by the Agency for Healthcare Research and Quality (AHRQ) as part of its 2022 PQI measures.[6] Diagnosis codes from administrative claims are used to flag the following conditions, which are the basis for the composite outcome variable:[7]

- PQI #1: Diabetes Short-Term Complications
- PQI #3: Diabetes Long-Term Complications
- PQI #5: COPD or Asthma in Older Adults
- PQI #7: Hypertension

[5] For example, “Simcor” contains two active substances: Simvastatin and Niacin. This is flagged as a statin because one of its active ingredients is a statin. Source for the FDA NDC directory: https://www.fda.gov/drugs/drug-approvals-and-databases/national-drug-code-directory
[6] For more information, see https://www.qualityindicators.ahrq.gov/modules/pqi_resources.aspx.
[7] Specifically, Hilltop defines these claims as those with a claim type of either 60 or 61 (indicating an inpatient claim) or a claim type of 40 (indicating an outpatient claim) and revenue center codes of 0450-0459 and 0981. Source: https://www.resdac.org/articles/how-identify-hospital-claims-emergency-room-visits-medicare-claims-data.

- PQI #8: Heart Failure
- PQI #11: Bacterial Pneumonia
- PQI #12: Urinary Tract Infection
- PQI #14: Uncontrolled diabetes
- PQI #15: Asthma in Younger Adults
- PQI #16: Lower-Extremity Amputation among Patients with Diabetes

This is implemented in the model as an indicator variable at the person-month level. If an individual incurs at least one avoidable hospitalization or ED visit in a given month, then that person receives a value of 1 for this variable—and 0 otherwise.

ii. The Hilltop Pre-DC Model™

The outcome measure in the Hilltop Pre-DC Model™ is a 0/1 indicator variable denoting whether an individual incurred a hospitalization or ED visit in a given month due to severe complications of type 2 diabetes. Both the Pre-AH Model™ and the Pre-DC Model™ include diabetes complications in the outcome that is predicted; however, the predicted outcome differs significantly across the two models, and the resulting risk scores are statistically distinct.[8] Severe complication of type 2 diabetes is indicated by the presence of one or more of the following ICD-10 diagnosis codes (in any position on the inpatient or ED claim) associated with severe complications of diabetes as defined by the Diabetes Complication Severity Index (DCSI):[9]

Retinopathy
Retinal detachments and breaks: H33.x
Type 2 diabetes mellitus with severe non-proliferative diabetic retinopathy: E11.34xx
Type 2 diabetes mellitus with proliferative diabetic retinopathy: E11.35xx
Blindness and low vision: H54.x
Vitreous hemorrhage: H43.1x

Nephropathy
Type 2 diabetes mellitus with chronic kidney disease (stage 4 or 5): E11.22, N18.4, N18.5
Type 2 diabetes mellitus with end stage renal disease: E11.22, N18.6
Unspecified kidney failure: N19

Cerebrovascular Complications
Nontraumatic intracerebral hemorrhage: I61.x
Cerebral infarction: I63.x
Occlusion and stenosis of precerebral arteries, not resulting in cerebral infarction: I65.x
Occlusion and stenosis of precerebral arteries, not resulting in cerebral infarction: I66.x
Acute cerebrovascular insufficiency: I67.81

[8] For additional information, see https://health.maryland.gov/mdpcp/Documents/PreDC_PreAH_Outcome_Distinction_Final.pdf
[9] Centers for Disease Control and Prevention, 2020; Chang et al., 2012; Glasheen et al., 2017

Cardiovascular Complications
Acute myocardial infarction (STEMI, NSTEMI): I21.x
Subsequent acute myocardial infarction (STEMI, NSTEMI): I22.x
Complications from acute myocardial infarction (STEMI, NSTEMI): I23.x
Old myocardial infarction: I25.2
Atrial fibrillation and flutter: I48.x
Cardiac arrest: I46.x
Paroxysmal tachycardia: I47.x
Other cardiac arrythmia: I49.x
Heart failures: I50x
Atherosclerosis of native arteries of the extremities with ulceration/gangrene: I70.25x, I70.26x
Aortic aneurysm/dissection: I71.x

Peripheral Vascular Disease
Gas gangrene: A48.0
Embolism and thrombosis of arteries of the lower extremities: I74.3
Non-pressure chronic ulcer of limb, not elsewhere classified: L97.x
Type 2 diabetes with diabetic peripheral angiopathy, with gangrene: E11.52
Gangrene, not elsewhere classified: I.96

Metabolic Complications
Type 2 diabetes mellitus with hyperosmolarity, with coma: E1101
Type 2 diabetes mellitus with ketoacidosis, with coma: E1111
Type 2 diabetes mellitus with hypoglycemia, with coma: E11641

iii. The Hilltop Pre-HE Model™

The outcome measure in the Hilltop Pre-HE Model™ is a 0/1 indicator variable denoting risk of eligibility for hospice for an individual. Hospice eligibility is defined at the person-month level as the presence of a date of death for a beneficiary in the Beneficiary Demographics file that is within six months of the last day of each person-month. Thus, for each beneficiary who has died, the flag for this event will be a 1 for the six months prior to that date. Table 2, below, shows an example of this.

Table 2. Example Scenario for Modeling Hospice Eligibility

	Jun 2020	Jul 2020	Aug 2020	Sep 2020	Oct 2020	Nov 2020	Dec 2020
Presence of a Date of Death	-	-	-	-	-	-	X
Hospice Eligibility Flag	0	1	1	1	1	1	1

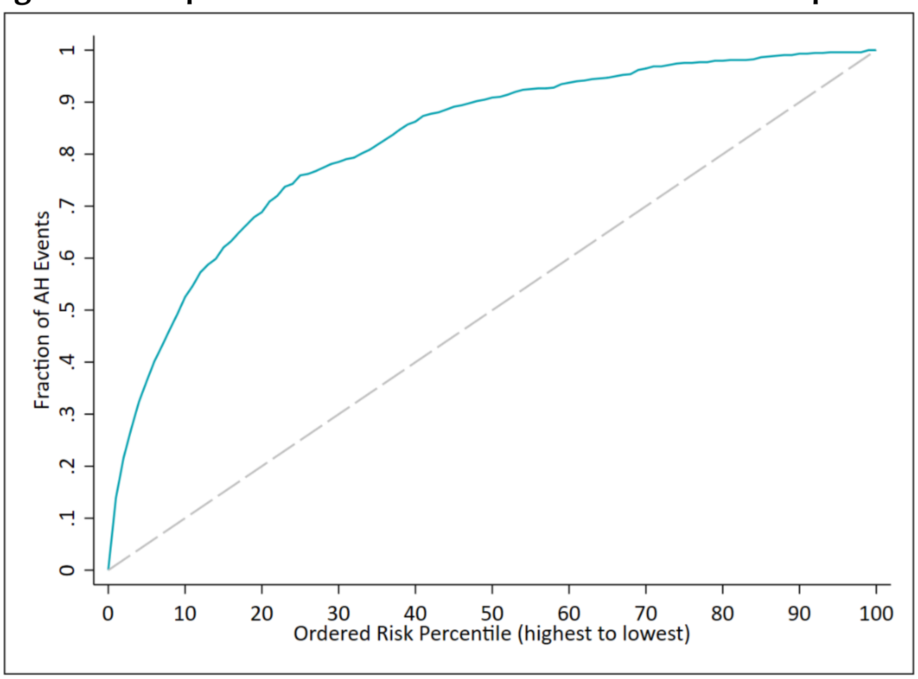
d. Model Performance

We assess the predictive power of the model using the *concentration curve*. In order to estimate the concentration curve, the patient cohort is ordered from most to least risky (in terms of predicted risk) on the X axis, and the fraction of total *actual* events captured by the riskiest patients on the Y axis. By comparing the predicted event risk scores to the actual occurrence of the predicted events, it is possible to evaluate the performance of the model.

i. The Hilltop Pre-AH Model™

In Figure 1, below, we present the concentration curve for the Hilltop Pre-AH Model™ by comparing risk scores released in April 2022 with actual avoidable hospital events incurred in May 2022. Approximately 47% of all individuals experiencing an avoidable hospital event in the following month are contained in the top 10% riskiest individuals as ranked by the Pre-AH Model™. We interpret this as strong performance of the model, and the other months show similar results (range: 47.8%-57.7%). These results imply that, if care managers were to focus their efforts on the top 10% riskiest beneficiaries each month, then they could reach almost half of all individuals experiencing avoidable hospital events that month.

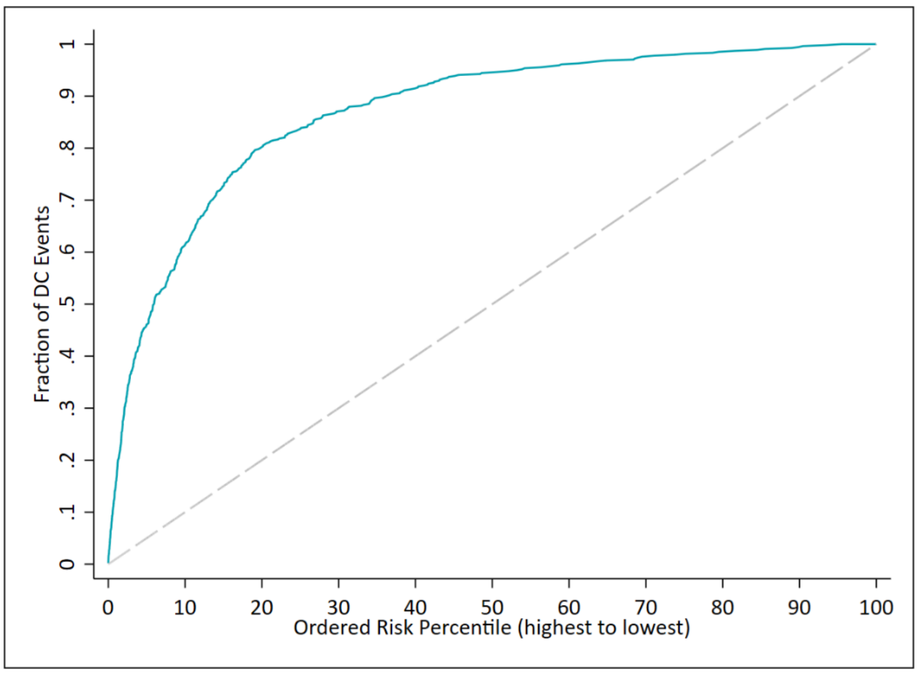
Figure 1. Hilltop Pre-AH Model™ Concentration Curve as of April 2022



ii. The Hilltop Pre-DC Model™

In Figure 2, below, we present the concentration curve for the Hilltop Pre-DC Model™ by comparing risk scores calculated as of April 2022 with actual severe diabetes complication events incurred in May 2022 (in the 20% holdout sample because the model was not in production as of this date). Approximately 61% of all individuals experiencing a severe type 2 diabetes complication event in the following month are contained in the top 10% riskiest individuals as ranked by the Pre-DC Model™. We interpret this as strong performance of the model, and the other months show similar results (range: 58%-63%). These results imply that, if care managers were to focus their efforts on the top 10% riskiest beneficiaries each month, then they could reach more than 60% of all individuals experiencing diabetes complication events that month.

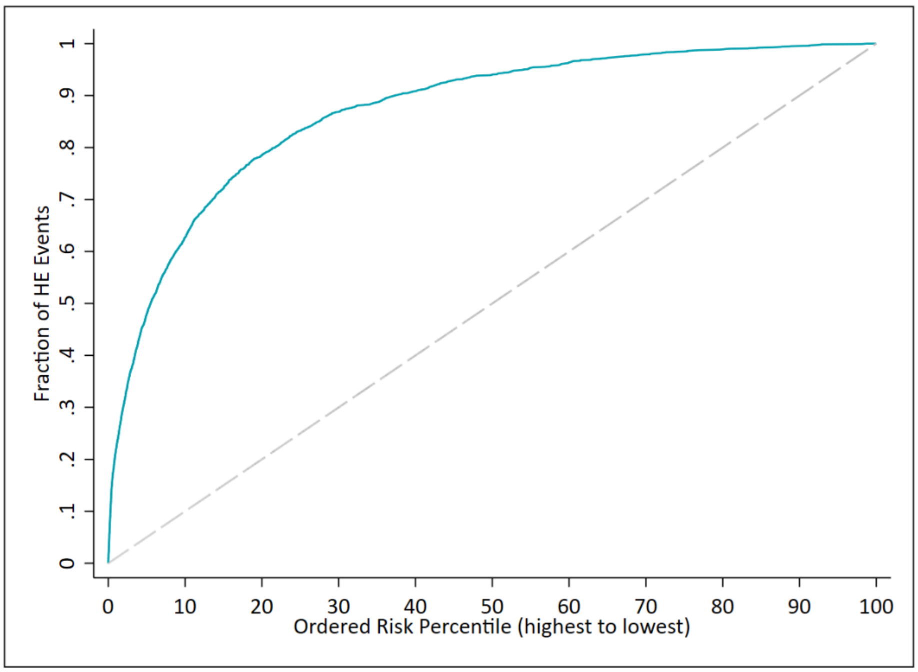
Figure 2. Hilltop Pre-DC Model™ Concentration Curve as of April 2022



iii. The Hilltop Pre-HE Model™

In Figure 3, below, we present the concentration curve for the Hilltop Pre-HE Model™ by comparing risk scores calculated as of October 2021 with actual outcome events incurred in November 2021 (in the 20% holdout sample because the model was not in production as of this date). Almost 63% of all individuals who may have been eligible for hospice care are contained in the top 10% riskiest individuals as ranked by the Pre-HE Model™. We interpret this as good performance of the model, and the other months show similar results (range: 61.9%-64.6%). These results imply that, if care managers were to focus their efforts on the top 10% riskiest beneficiaries each month, then they could reach more than 60% of the patients who may be appropriate candidates for hospice care to proactively begin advanced care discussions.

Figure 3. Hilltop Pre-HE Model™ Concentration Curve as of December 2021



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