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When People Don't Know Their Numbers: Exploring an Approach to Choosing Proxy Biometrics in Cardiovascular Disease Risk Assessment

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Abstract

Scope: To explore an approach to identifying proxy biometric values from population health data to be used in Cardiovascular Disease (CVD) risk assessment when individuals do not know their numbers.

Methodology: Proxy biometric values for Systolic Blood Pressure (SBP), Total Cholesterol (TC), and High-Density Lipoprotein (HDL) cholesterol were created using data from the National Health and Nutritional Examination Survey 2015-2016 dataset stratifying by age group, sex, race/ethnicity, and biometric level. These proxy biometric values were assigned to individuals who completed the WellSuite® IV Health Risk Assessment (HRA) for the Workforce based on their demographics and biometric level. Paired sample t-tests were used to evaluate differences between proxy biometric values and those reported in the HRA as well as the 10-year CVD risk based on either biometrics.

Findings: Proxy biometric values for SBP, TC, and HDL cholesterol were statistically significantly different from those reported in the HRA. Proxy biometric values performed better in some subgroups than others. The 10-year CVD risk based on proxy biometric values were also significantly different from risk based on biometrics reported in the HRA, however, only 7.4% of HRA participants changed CVD risk levels.

Conclusion: Using proxy biometric values from population health data may be one solution to assessing CVD risk when individuals do not know their numbers but only when done outside the healthcare setting. Future research is needed.

Limitations: The populations from which the data are derived differed, and decisions regarding the assignment of proxy biometric values may have contributed to the statistically significant differences between biometric values and CVD risk.

Keywords: Blood pressure • Cholesterol • Risk assessment • Population health • Methods

Abbreviations: ACC: American College of Cardiology; AHA: American Heart Association; AI: American Indian; AN: Alaskan Native; CI: confidence Interval; CVD: Cardiovascular Disease; dL: deciliter(s); GED: General Educational Diploma; HDL: High-Density Lipoprotein; HRA: Health Risk Assessment; mg: milligram(s); mmHG: millimeters of Mercury; NA: Not Applicable; NHANES: National Health and Nutrition Examination Survey; NR: Not Reported; PCE: Pooled Cohort Equation; PI: Pacific Islander; SBP: Systolic Blood Pressure; TC: Total Cholesterol

Introduction

Biometrics, such as blood pressure, cholesterol, and glucose, are an integral component to assessing an individual's health as they are indicators for underlying health issues such as hypertension and diabetes. Biometrics is also used in risk calculators to estimate an individual's risk for chronic conditions such as Cardiovascular Disease (CVD) [1] or diabetes [2]. These risk calculators or assessments, however, often require actual biometric numbers to estimate risk and many individuals do not know their numbers. For example, one study reported that 50% of individuals did not know their blood pressure and 79% did not know their cholesterol values when using an online heart risk calculator [3]. Although an individual may not know their exact biometric values, they may know in which level their biometrics fall such as having normal blood pressure or high cholesterol. This information can be valuable when assessing health risks as it could inform proxy biometric values to be used in risk assessment; however, there is currently no guidance on how to select an individual's biometric proxy values based on their self-reported biometric levels. The aim of this study is to explore an approach to identifying proxy biometric values using population health data and evaluating the accuracy of these proxy biometric values by comparing it to clinically or self-reported biometrics reported in a Health Risk Assessment (HRA) and when used in CVD risk assessment.

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Materials and Methods

Data sources

National Health and Nutrition Examination Survey Data (NHANES): To create proxy biometric values, we used population health data from the National Health and Nutrition Examination Survey[16] (NHANES) 2015-2016 dataset which provides demographic, examination, and laboratory data (Centers for Disease Control and Prevention and National Center for Health Statistics). We included individuals' ages 40-79 years as this is the population in which CVD risk calculators are validated and can be used.

We stratified survey participants by 5- and 10-year age groups, sex, race/ethnicity, and biometric level (i.e., low, normal, elevated, and high). We used the age at the time of the screening interview to define the 5- and 10-year age groups in which a participant fell. We used the race and Hispanic origin information that included a non-Hispanic Asian category to define an individual's race/ethnicity. We also combined the Mexican American and other Hispanic categories into one category (Hispanic).

Per NHANES protocol, up to four blood pressure values could be reported to obtain an accurate blood pressure measurement. Three consecutive blood pressure measurements were required, but if one was interrupted or incomplete, a fourth attempt was made. Following guidelines from the American Heart Association (AHA) on blood pressure measurement, we took the average of all blood pressure measurements to designate a single blood pressure value [4,5]. We defined biometric levels using published guidelines. All biometrics were categorized in low, normal, elevated, and high, where appropriate. Systolic blood pressure (SBP) levels were defined using joint guidelines on blood pressure measurement: low (less than 90 mm Hg), normal (90-119 mm Hg), elevated (120-129 mmHg), and high (130 mmHg or higher) [5]. Total cholesterol (TC) levels were defined using the National Heart, Lung, and Blood Institute (NHLBI) guidelines for the detection, evaluation, and treatment of high cholesterol: low (less than 150 mg/dL), normal (150-199 mg/dL), elevated (200-239 mg/dL), and high (240 mg/dL or higher) [6]. High-Density Lipoprotein (HDL) cholesterol levels were defined using NHLBI guidelines: for males, low (less than 40 mg/dL) and normal (40 mg/dL or higher); and for females, low (less than 50 mg/dL) and normal (50 mg/dL or higher) [6]. We calculated the mean and median values for SBP, TC, and HDL cholesterol stratified by 5- and 10-year age groups, sex, race/ethnicity, and biometric level. We truncated the averages for SBP as rounding leads to over- and under-recording of blood pressure and end digit preference.

Health risk assessment data

We used de-identified data collected between January 1, 2018 and December 31, 2018 from the WellSuite IV Health Risk Assessment for the Workforce (Wellsource). We included data from the most recently completed HRA of unique individuals in the timeframe specified. We limited the HRA participants eligible for CVD risk assessment; therefore, we included adult's ages 40-79 years who had provided enough data to allow their CVD risk to be calculated.

We excluded individuals with a history of coronary heart disease or stroke as estimating CVD risk is intended for those without a previous history. We also excluded pregnant women as biometrics while pregnant largely differ from those when not pregnant.

Biometrics in the HRA may have been directly derived from the participant's health record (clinically reported) or could have been provided through self-report. When both clinically- and self-reported biometrics were reported, we prioritized clinically reported values over self-reported ones for the best available biometric value. We defined biometric levels using published guidelines [5,6] as described above.

Proxy biometric values

We assigned each HRA participant proxy biometric values for SBP, TC, and HDL cholesterol from NHANES data based on their age, sex, race/ethnicity, and biometric level (as determined by the best available biometric reported in the HRA). We used the age at the time of the HRA to define the 5- and 10-year age groups in which a participant fell. The HRA included more race/ethnicity options than the NHANES survey. For those who identified as American Indian or Alaskan Native, or Other race in the HRA, we assigned biometrics from those who identified as other race in NHANES. For those who indicated they did not want to report their race/ethnicity or those that did not know their race/ethnicity, we assigned biometrics from the total population for that age, sex, and biometric level group. When a proxy biometric value was not available for a particular age, sex, race/ethnicity, and biometric level, we assigned the biometrics from the total population for that age, sex, and biometric level as we tried to closely match the individual to an appropriate proxy biometric value as possible.

Cardiovascular disease risk assessment

Using the AHA and American College of Cardiology (ACC) Pooled Cohort Equation (PCE) for atherosclerotic CVD risk [1], we calculated each HRA participant's 10-year CVD risk using the best available biometric reported in the HRA. We also calculated the 10-year CVD risk using the proxy biometric values that performed best when compared to the best available biometric reported in the HRA—that is, was not statistically significantly different from the HRA biometric values and/or had the smallest mean difference from the HRA biometric values. We also stratified HRA participants by CVD risk level: low (<5%), borderline (5%-7.4%), intermediate (7.5%-19.9%), and high (≥20%) [1].

Data analysis

We used chi-square statistics and independent sample t-tests to compare the baseline characteristics of the NHANES and HRA participants. We defined statistical significance between groups as a p-value less than 0.05. We analyzed the accuracy of the proxy biometric values by comparing those derived from NHANES data to the best available biometric value as reported in the HRA. We calculated the difference and absolute difference. Descriptive statistics are reported (e.g., mean, range). We also analyzed the differences using paired sample t-tests. We reported mean differences, 95% Confidence Intervals (CI), and p-value. We defined statistical significance as a p-value less than 0.05. Subgroups analyses were conducted by age, sex, race/ethnicity, HRA biometric type (clinically reported or self-reported), biometric level, and excluding HRA biometric outliers.

We also analyzed the accuracy of the proxy biometric values when used in the ACC/AHA PCE for atherosclerotic CVD risk [1] by comparing risk when using the proxy biometric value that performed best to the risk when using the best available HRA biometric data. We analyzed the differences using paired sample t-tests. We reported mean differences, 95% Confidence Intervals (CI), and p-value. We defined statistical significance as a p-value less than 0.05. We also determined the number of individuals whose CVD risk level changed because of using proxy biometrics compared to the best available biometrics in the HRA. All data were managed, and analyses were conducted in SPSS statistical software (IBM®).

Results

Baseline characteristics

The NHANES cohort consisted of 3,297 individuals and the HRA data included 23,352 participants. The baseline characteristics for the NHANES and HRA participants are provided in Table 1. There were statistically significant differences across all characteristics between the two groups ($p<0.01$). The HRA participants were younger, more often female, White, and college-educated compared to the NHANES participants (all $p<0.01$).

Table 1. Baseline demographics and biometrics.

Demographic	National Health and Nutrition Examination Survey (NHANES), 2015-2016	Wellsource health risk assessment*
n	3,267	23,352
Age, mean	57.6 (range, 40-79)	52.3 (range, 40-79)
Sex	Male: 1,573 (48.1%)	Male: 6,088 (26.1%)
	Female: 1,694 (51.9%)	Female: 17,264 (73.9%)
Race	White: 1,020 (31.2%)	White: 18,031 (77.2%)
	Black: 727 (22.3%)	Black: 2,326 (10.0%)
	Hispanic: 1,049 (32.1%)	Hispanic: 642 (2.7%)
	Asian: 366 (11.2%)	Asian: 1,105 (4.7%)‡
	Other: 105 (3.2%)†	Other: 1,248 (5.4%)§
Education**	Less than 9th grade: 461 (14.1%)	Less than 9th grade: 18 (0.1%)
	9th-11th grade: 405 (12.4%)	9th-11th grade: 60 (0.3%)
	High school diploma or GED: 696 (21.3%)	High school diploma or GED: 2,493 (10.7%)
	Some college: 908 (27.8%)	Some college: 8,067 (34.5%)
	Bachelor's degree or higher: 796 (24.4%)	Bachelor's degree or higher: 12,316 (52.7%)
	Not reported: 1 (0.03%)††	Not reported: 398 (1.7%)††
Systolic blood pressure (mm Hg), mean	129 (range, 85-231)	120 (range, 50-200)‡‡
Total cholesterol (mg/dL), mean	195.72 (range, 81-545)	190.78 (range, 50-2,676)‡‡
High-density lipoprotein cholesterol (mg/dL), mean	54.35 (range, 6-226)	58.72 (range, 15-199)‡‡
10-year CVD risk, %	Not reported	3.43 (range, 0.02-55.18) §§

CVD: Cardiovascular Disease; dL: deciliter; GED: General Educational Diploma; mg: milligrams; mmHg: Millimeters of Mercury. *: Limited to participants with complete data and eligible for CVD risk assessment, †: Other races not defined, ‡: Includes Pacific Islanders, §: Includes American Indian or Alaskan Natives, and individuals who reported they do not know their race or did not want to say, **: For NHANES, includes data among those ages 20 years or older, ††: Includes missing data and 01 those who reported they do not know their education level, ‡‡: Includes clinically reported or self-reported values, §§: Based on ACC/AHA PCE for atherosclerotic CVD risk using the best available biometric data from the HRA.

The biometrics were also statistically significantly different ($p<0.01$); the HRA participants had lower SBP, lower TC, and higher HDL cholesterol than NHANES participants. Clinically reported values for SBP, TC, and HDL cholesterol were used as the best available in 13,025, 13,008, and 13,001 HRA participants, respectively. Self-reported values were used as the best available for SBP, TC, and HDL cholesterol in 10,327, 10,344, and 10,351 HRA participants, respectively. A little more than half (55.6%) of the HRA participants had clinically reported values for all three biometrics.

Proxy biometric values

Mean and median proxy biometric values for SBP, TC, and HDL cholesterol, as derived from NHANES data, stratified by 5 and 10-year age group, sex, race/ethnicity, and biometric level are available in Appendix 1.

Evaluation of proxy biometric values

The mean differences between the proxy biometric values and the best available biometric reported in the HRA are reported in Table 2. Across all biometrics, the mean differences were close to zero, and the ranges of the differences were wide, showing that the proxy biometric values were both under- and overestimating the best available biometrics reported in an HRA. Absolute differences showed, on average, that proxy biometric values were off by about 5 mm Hg for SBP, 12.42 mg/dL for TC, and 9.69 mg/dL for HDL cholesterol (data not shown). All differences between proxy biometrics values and the best available as reported in the HRA (Table 2), except the median proxy biometric values for TC and the mean proxy biometric values for HDL cholesterol, were statistically significant. Subgroup analyses based on age, sex, race/ethnicity, biometric used from the HRA, biometric level, and excluding outliers showed similar differences (Appendix 2), although there were more frequent differences that were not statistically significant. Proxy biometric values were more often similar to those reported in the HRA among females, Asian/Pacific Islanders, Alaskan Native/American Indians, those aged 74-79 years, and when using clinically reported values only.

Table 2. Accuracy of proxy biometrics compared to clinically or self-reported biometrics in a health risk assessment. HDL: High-Density Lipoprotein Cholesterol; SBP: Systolic Blood Pressure; TC: Total Cholesterol *: $p<0.05$, paired sample t-test.

Biometric	Proxy value used	Mean difference (95% CI)	Range of differences
SBP, mmHg	10-year age group, mean	0.43 (0.34 to 0.52)*	-61 to 38
	10-year age group, median	0.39 (0.30 to 0.47)*	-65 to 38
	5-year age group, mean	0.32 (0.23 to 0.41)*	-61 to 45
	5-year age group, median	0.31 (0.23 to 0.40)*	-65 to 37
TC, mg/dL	10-year age group, mean	0.55 (0.24 to 0.87)*	-2,406.82 to 91.00
	10-year age group, median	0.09 (-0.23 to 0.41)	-2,420.00 to 92.50
	5-year age group, mean	0.75 (0.43 to 1.06)*	-2,399.33 to 94.33
	5-year age group, median	0.26 (-0.06 to 0.59)	-2,415.50 to 96.00
HDL, mg/dL	10-year age group, mean	0.03 (-0.15 to 0.20)	-136.92 to 27.72
	10-year age group, median	-2.96 (-3.13 to -2.77)*	-139.00 to 29.00
	5-year age group, mean	-0.15 (-0.33 to 0.03)	-138.18 to 27.78
	5-year age group, median	-2.83 (-3.01 to -2.65)*	-139.00 to 28.00

Evaluation of proxy biometric values in CVD risk assessment

The 10-year CVD risk based on the best performing proxy biometrics (i.e., median 5-year for SBP, median 10-year for TC and mean 10-year for HDL cholesterol) was statistically significantly different from the 10-year CVD risk based on the best available biometrics reported in the HRA (mean difference, 0.06 (95% CI, 0.01 to 0.05, $p<0.001$). When participants were stratified into CVD risk levels, 7.4% of HRA participants moved into

a different risk level when proxy biometric values were used instead of the best available reported in the HRA (Table 3).

Table 3. Cardiovascular disease risk stratification based on biometric value used: proxy biometric value or best available in the health risk assessment.

10-year CVD risk using best available biometrics in the HRA	10-year CVD risk using best performing proxy biometric values				Total
	Low	Borderline	Intermediate	High	
Low	18,100 (77.5%)	364 (1.6%)	20 (0.1%)	0 (0%)	18,484 (79.2%)
Borderline	547 (2.3%)	1,364 (5.8%)	276 (1.2%)	0 (0%)	2,187 (9.4%)
Intermediate	31 (0.1%)	378 (1.6%)	1,960 (8.4%)	48 (0.2%)	2,417 (10.4%)
High	1 (0.0%)	1 (0.0%)	61 (0.3%)	201 (0.9%)	264 (1.1%)
Total	18,679 (80.0%)	2,107 (9.0%)	2,317 (9.9%)	249 (1.1%)	23,352 (100%)

Discussion

The proxy biometric values derived from population health data both under- and overestimated those reported in the HRA. On average, they differed from the best available biometrics from the HRA by about 5 mm Hg for SBP, 12.42 mg/dL for TC, and 9.69 mg/dL for HDL cholesterol. Statistical testing showed proxy biometric values were significantly different from those reported in the HRA except the median proxy biometric values for TC and the mean proxy biometric values for HDL cholesterol. Proxy biometric values performed better in some subgroups than others. When the best performing proxy biometrics were used in CVD risk assessment, the resulting 10-year CVD risk was statistically significantly different from the 10-year CVD risk based on the best available biometrics reported in the HRA. Only 7.4% of HRA participants, however, changed their risk level when proxy biometrics were used instead of the best available biometrics reported in the HRA. This gives some confidence that proxy biometric values can be used in place of actual biometric data in CVD risk assessment as less than 10% of individuals moved into a different risk level. This confidence is based on most clinical decision-making in the prevention of CVD relying on CVD risk such as using a daily aspirin if an individual whose 50-59 years old and has CVD risk is greater than 10% [7]. When risk is communicated outside the healthcare setting—such as an individual using an online heart risk calculator to determine if they should schedule an appointment with a healthcare provider or to learn more about their health risks—using proxy values may accurately represent their true risk when they don't know their health numbers. Although this study provides some confidence that proxy biometric values can be used in risk assessment when someone does not know their numbers, it is imperative that individuals know their numbers. They should be aware of their cholesterol, blood pressure, blood sugar, and body mass index as these are critical to understanding physical wellbeing [8]. Knowing health numbers will allow for more accurate risk assessment and decision-making outside of healthcare (as it is expected clinically measured values would and should be used in the healthcare setting for clinical decision-making). There should be population health efforts to address the multitude of reasons for not knowing health numbers including campaigns to increase awareness of the importance of knowing health numbers, making biometrics results more easily accessible and readily available, and increasing access to healthcare services [9] since most biometrics require a trained clinician, device, or laboratory test to measure them.

Limitations

There are several limitations that likely contributed to the statistically significant differences between the proxy biometric values and those reported in the HRA, which subsequently contributed to the differences in CVD risk. The first and foremost being the populations from which proxy and actual biometric values were derived and compared were statistically significantly different. This likely occurred for a few reasons. One being that NHANES is designed to be representative of the national U.S. population while the HRA was designed for those in the workforce. Most individuals who completed the HRA likely did so through their employer's wellness program or health plan. The HRA population may have been healthier than the nationally representative population as studies have shown employment [10,11] and access to health insurance [12,13] have positive health outcomes. Another reason for the differences in populations was the less stringent exclusion criteria applied to the NHANES dataset possibly contributing to the healthier status of the HRA population. Although we limited the age of both datasets to those 40-79 years, the NHANES dataset included pregnant women, those with a personal history of CVD, and those using medications that may affect biometrics and CVD risk. Excluding these participants from the NHANES dataset may have made them more like the participants who completed the HRA, although it would mean a smaller cohort. Another limitation was the approach to creating and selecting the proxy biometric values. First, we stratified NHANES participants by age group, sex, race/ethnicity, and biometric level. Such precision resulted in there being small sample sizes in each stratification, and in some cases, no participants. For example, there were no White females aged 40-49 years with low SBP and only two Asian males aged 60-69 years with high cholesterol. A larger population size per stratification would allow more confidence in the proxy value biometric being calculated. It would also allow for further stratification such as by use of blood pressure or lipid-lowering medication which would affect biometrics and CVD risk. When assigning a proxy biometric value, in the case of stratifications that had no individuals, we selected the proxy biometric value from the total population for that age group, sex, and biometric level, which was a biometric that was more representative of the larger population, not that specific subgroup. Similarly, for stratifications with small sample sizes, the proxy biometric value selected might not have been representative of that subgroup as there were too few individuals represented in it. Confidence intervals of the proxy biometric values were often wide (data not shown). For example, the 95% CI for high cholesterol among Asian men aged 60-69 years was 129.38-421.62 mg/dL as there were only two individuals represented in this stratification. Wide CIs reflect a small sample size and again lowers the confidence in the precision of the proxy biometric value being used to represent the biometric of that subgroup. And finally, the biometrics provided in the HRA data were either clinically reported or self-reported values which may have contributed to the large differences. Clinically reported values were derived from the individual's health record. Although there are no details regarding the protocol or measurement process of these biometrics, there is more confidence in the reliability of these values compared to those that were self-reported as the latter are often inaccurate [14, 15]. When compared to clinically reported values only, the proxy biometric values were no longer statistically significantly different for SBP and TC, but remained significantly different for HDL cholesterol. This finding is encouraging as it shows proxy biometric values can be used as estimates for clinical biometrics.

Recommendations for Future Studies

Future research is needed to evaluate the creation, selection, and use of proxy biometric values when an individual does not know their numbers as it is possible some approaches to creating and selecting a proxy biometric value may be more accurate for some populations or for certain biometrics than for others. These studies should derive the proxy biometrics values from different population health datasets or cohorts, preferably those with larger sample sizes that allow subgroup stratification. They should also evaluate proxy biometric values in other subgroups or stratifications not included in this study, such as those ages 18-39 years and those using blood pressure or lipid-lowering medications. They should evaluate other biometrics such as low-density lipoprotein cholesterol, glucose, and diastolic blood pressure as these are often used in risk calculators. And future studies should evaluate the use of proxy biometric values in the risk assessment of other chronic conditions in addition to CVD.

Conclusion

While proxy biometric values may provide a good estimate to an individual's CVD risk when they do not know their health numbers, more research is needed to have more confidence in the results. Population health efforts should be in place to help people know their numbers.

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