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# Manuscript Submission: Temporal trends and disparities in Metabolic Syndrome prevalence (2015–2025): a dual-scale analysis of Electronic Health Records data

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**Article**

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# Manuscript Submission: Temporal trends and disparities in Metabolic Syndrome prevalence (2015–2025): a dual-scale analysis of Electronic Health Records data

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## Abstract

### Background

Understanding temporal trends in Metabolic Syndrome (MetS) prevalence is essential for public health planning especially following macro-environmental shocks. The objective of this study was to quantify the annual percentage change (APC) and annual percentage point change (APPC) in the prevalence of MetS in Indiana, United States.

### Methods

Retrospective serial cross-sectional study utilizing electronic health records data between 2015 and 2025. Exposures included time (years), age, sex, and race/ethnicity. The primary outcomes were MetS prevalence, the APC and APPC in prevalence.

### Results

MetS prevalence increased from 21.4% in 2015 to 35.1% in 2025. The cohort-wide relative trend was stable with APC of 4.8% [4.5%–5.1%]; $p<0.001$. Overall pre-pandemic absolute growth (APPC=0.90, 2015–2020) nearly doubled following a 2020 structural break (APPC=1.71, 2020–2025; p=0.005). Accelerations were concentrated in younger cohorts: adolescents (ages 12-19; APPC 0.10 to 0.88, p<0.001) and young adults (ages 20-39; APPC 0.70 to 2.05, p=0.001), while older adults maintained uninterrupted growth. Divergent structural shocks emerged by race/ethnicity, with significant post-2020 accelerations among NH White (APPC 0.97 to 2.04, p=0.010), NH Asian (APPC 1.10 to 1.72, p=0.041), and NH AI/AN (APPC -0.25 to 1.61, p=0.030) populations. In contrast, NH Black and Hispanic/Latino cohorts exhibited continuous high growth without discrete pandemic breakpoints.

### Conclusions

MetS prevalence rose between 2015 and 2025, with an absolute breakpoint around 2020/21. The systemic shock disproportionately changed trends of certain demographics including adolescents and young adults. Population surveillance could benefit by tracking absolute volume expansions alongside relative rates to guide targeted, equitable structural interventions.

**Key words**: Metabolic Syndrome, MetS, Annual percentage change, Annual point percentage change, relative scale, absolute scale, inflection point

## Introduction

Metabolic syndrome (MetS) is a clustering of interrelated cardiometabolic risk factors including central obesity, elevated blood pressure, dyslipidemia, and impaired glucose metabolism that collectively elevate the risk of cardiovascular disease, type 2 diabetes, and all-cause mortality [1, 2]. In the United States, the prevalence of MetS has risen steadily over the past two decades, reflecting broader secular trends in obesity, sedentary behavior, and dietary risk [3, 4]. National estimates from the National Health and Nutrition Examination Survey (NHANES) suggest that more than one-third of US adults meet the criteria for MetS, with a disproportionate burden borne by older adults, men, and specific racial and ethnic minority groups [3, 5, 6].

Despite its clinical and public health significance, population-level surveillance of MetS remains constrained by reliance on cross-sectional national surveys [7, 8]. While these surveys successfully track broad relative trends, they lack the temporal granularity required to detect acute, absolute shifts in healthcare burden following macro-environmental shocks. Electronic Health Record (EHR) data offers a complementary architecture for surveillance, enabling large-scale, geographically specific, and temporally precise monitoring of chronic diseases [9, 10]. These data could be leveraged to evaluate long-term trends in MetS prevalence pre and post COVID-19 pandemic [9, 11, 12].

The pandemic introduced disruptions to healthcare access, physical activity, dietary patterns, and chronic disease management, all of which may have accelerated underlying cardiometabolic risk [13-15]. To determine whether these disruptions translated into measurable structural shifts in population-level metS prevalence, this study utilizes continuous EHR data from a statewide health information exchange to evaluate trends of MetS from 2015 to 2025. A dual-scale analytic framework was applied to assess both relative metrics, the annual percentage change (APC) and absolute metric, the annual percentage point change (APPC). The following two hypotheses were formally tested:

1. The compounding relative rate of prevalence quantified by APC remained stable between 2015 and 2025.
2. The absolute prevalence trajectory quantified by APPC did not experience a significant shift following the onset of COVID-19 pandemic.

## Methods

### Study design and data source

A retrospective serial cross-section study that used data from the Indiana Network for Patient Care (INPC), a statewide health information exchange (HIE) network that links and aggregates data from hospitals, outpatient clinics, emergency departments, laboratories, and community health centers across Indiana [16, 17]. Data from the INPC are routinely leveraged for population health studies and public health uses[18, 19] in addition to uses by clinicians for routine patient care.

Data from the two largest health systems that together provide care to >70% of residents in Central Indiana and serve patients from all 92 counties were used. One system includes multiple hospitals, emergency departments, urgent care centers, and a large network of primary and specialty clinics. The second system includes a major urban hospital, an emergency department, specialty clinics, and a network of community health centers. Across these systems, approximately 2.4 million unique individuals contributed data during the study period. This sample represents approximately 36.0% of

the total state population age 2 or more years as of 2025. All patients with at least two clinical encounters between 2015 and 2025 were included.

## MetS definition

MetS was defined using harmonized criteria by the International Diabetes Federation (IDF) and American Heart Association/National Heart, Lung, and Blood Institute (AHA/NHLBI) [2]. Patients were classified as having MetS in a given calendar year if they met at least three of five components of central obesity, elevated triglycerides, reduced high-density lipoprotein (HDL) cholesterol, elevated blood pressure (BP), and elevated fasting glucose or impaired glycemic control.

Because waist circumference was not routinely available in the INPC, central obesity was approximated using body mass index (BMI). For adults, it was defined as BMI≥30 kg/m² and for children and adolescents, as BMI≥95th percentile for age and sex. Elevated triglyceride was defined as ≥150 mg/dL or on triglyceride-lowering medication and reduced HDL cholesterol as <40 mg/dL for men and <50 mg/dL in women or on HDL-raising medication. Elevated BP was defined as systolic BP≥30 mmHg or diastolic BP≥85 mmHg on at least two different days within a two-year window, a diagnosis code for hypertension, or active prescription of antihypertensive medication. Elevated glucose was defined as fasting plasma glucose ≥100 mg/dL, hemoglobin A1c>5.7%, a diagnosis code for type 2 diabetes, or active prescription of glucose-lowering medication.

Exposures included time (years), age, sex, and race/ethnicity. The primary outcomes were MetS prevalence, the APC and APPC in prevalence.

## Data preparation

All data were summarized at the patient-year level. Indicator variables were created for the presence of each MetS component. The total number of components ranged between 0 and 5 and patients with 3 or more were classified as having MetS. Annual prevalence (overall and demographic stratified) was calculated using the number of patients with MetS as the numerator and the total number of patients in the sample as denominator. Age-adjusted prevalence was calculated using direct standardization to the 2000 U.S. standard population.

## Statistical analysis of temporal trends

The Annual Percent Change (APC) estimated the relative rate of change and was calculated using a log-linear regression model $\log(\text{prevalence}) = \beta_0 + \beta_1 \times \text{Year}$. The Davies' test was used to test for the null hypothesis ($H_0: \beta_{\text{diff}} = 0$) of a constant relative slope. Interaction terms $(\text{Year} \times \text{demographic stratum})$ were subsequently added to test for within differences in the rate of change by demographic characteristics.

Interrupted time-series analysis using linear spline regression models evaluated the absolute physical volume of expansion and tested for shifts surrounding the COVID-19 pandemic (disruption in healthcare utilization, screening, and real-world diagnostic workflows) with a fixed knot at 2020. For each demographic, APPC was modeled using: $Y = \beta_0 + \beta_1(\text{Years}_{\text{Pre}}) + \beta_2(\text{Years}_{\text{Post}}) + \epsilon$, where$= \text{Years}_{\text{Post}} = \max(0, \text{Year} - 2020)$. This allowed the extraction of the pre-pandemic slope (2015–2020), the post-pandemic slope (2020–2025), and 95% confidence intervals.

Trend significance within each period was evaluated using a two-tailed $t$-test ($H_0$:APPC $= 0$) and the slope difference between post-2020 and pre-2020 ($H_0$: $\text{APPC}_{\text{post}} - \text{APPC}_{\text{pre}} = 0$) tested for a breakpoint of a steady trend. To validate the selection of the 2020 breakpoint, sensitivity analysis was conducted by iteratively shifting the fixed breakpoint annually from 2020 through 2023, evaluating the comparative strength of the slope difference ($\mathbf{p}$-values) across demographic strata. Analyses were conducted using R (version 4.5.1).

**Approval for animal or human experiments**: This study did not involve any animal or human experiments.

**Consent for publication**: Not applicable. This manuscript does not contain any individual person's identifiable details, images, or videos. The electronic health record (EHR) data used for this retrospective study were fully de-identified, contained no Protected Health Information (PHI), and relied entirely on pseudo-generated patient IDs. Consequently, obtaining individual consent for publication was neither feasible nor deemed necessary. Due to retrospective nature of the study, informed consent was waived by the Human Research Protection Program (HRPP) at Indiana University (Protocol # 2010317218) as Category 4(iii) of the 45 CFR 46 (Revised Common Rule).

## Results

### Study Population

The cohort (Table 1) included 2,393,932 unique patients, 53.1% females and by race/ethnicity White (69.9%), Black (13.8%), Hispanic/Latino (8.3%), Asian (2.7%), AI/AN (0.09%), NHOPI (0.09%), multi-racial (2.3%), and Other Race (2.8%).

**Table 1: Patient (sample) characteristics**

| Demographic | Group | Size | Percentage |
|---|---|---|---|
| Age group | 2-5 | 273,709 | 11.43 |
| | 6-11 | 181,821 | 7.60 |
| | 12-19 | 270,399 | 11.30 |
| | 20-39 | 698,602 | 29.18 |
| | 40-59 | 546,917 | 22.85 |
| | 60-79 | 364,412 | 15.22 |
| | 80+ | 58,072 | 2.43 |
| Sex | Females | 1,270,525 | 53.07 |
| | Males | 1,123,407 | 46.93 |
| Race/ethnicity* | NH White | 1,673,497 | 69.90 |
| | NH Black | 330,549 | 13.81 |
| | Hispanic/Latino | 197,661 | 8.26 |
| | NH Asian | 65,371 | 2.73 |
| | NH Multiple races | 54,789 | 2.29 |
| | NH AI/AN | 2,228 | 0.09 |
| | NH NHOPI | 2,131 | 0.09 |
| | NH Other Race | 67,706 | 2.83 |
| **Total** | | **2,393,932** | **100.00** |

**NH=Non-Hispanic*

## Prevalence of MetS

Age-adjusted **MetS** prevalence increased from 21.4% (2015) to 35.1% (2025), representing a relative increase of 64% (Table 2). The crude prevalence was similar to age-adjusted estimates, indicating minimal confounding by age. Prevalence rose with age, from <1% in children (2–5 years) to >50% in adults aged 60–79 and 80+ years by 2025, and increased across all age groups, except for 2-5 years. Both genders experienced substantial increases in prevalence, with males exhibiting slightly higher rates. The largest percentage-point increases occurred among White (15.7), Asian (14.8), and NHOPI (13.5) populations, while the smallest absolute increase was observed among the American Indian/Alaska Native (7.1) population.

Table 2: Crude (for age) and age-standardized **MetS** prevalence (2015-2025)

| Demographic | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | 2024 | 2025 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| All | 21.4 | 23.5 | 24.4 | 24.7 | 26.5 | 26.2 | 27.7 | 30.4 | 32.5 | 33.8 | 35.1 |
| **Age group** | | | | | | | | | | | |
| 2-5 | 0.8 | 0.7 | 0.7 | 1.0 | 0.8 | 0.6 | 0.6 | 0.7 | 0.8 | 0.8 | 0.9 |
| 6-11 | 3.4 | 3.7 | 3.9 | 3.8 | 4.4 | 4.2 | 4.9 | 4.8 | 5.0 | 5.1 | 5.7 |
| 12-19 | 7.1 | 7.3 | 7.9 | 7.6 | 7.9 | 7.5 | 8.8 | 9.5 | 10.4 | 11.3 | 12.3 |
| 20-39 | 15.3 | 17.0 | 17.8 | 18.2 | 20.2 | 18.6 | 20.8 | 23.6 | 26.1 | 27.9 | 29.5 |
| 40-59 | 28.6 | 31.5 | 33.4 | 33.4 | 36.7 | 36.1 | 38.5 | 42.4 | 45.0 | 46.6 | 46.3 |
| 60-79 | 32.4 | 35.2 | 37.8 | 37.4 | 41.9 | 44.4 | 46.1 | 51.4 | 53.9 | 55.5 | 54.5 |
| 80+ | 28.3 | 30.4 | 32.8 | 31.7 | 35.6 | 39.2 | 41.6 | 47.4 | 50.1 | 52.0 | 51.7 |
| **Sex** | | | | | | | | | | | |
| Female | 19.9 | 22.0 | 23.3 | 23.4 | 25.3 | 24.8 | 26.6 | 29.8 | 32.2 | 33.8 | 34.8 |
| Male | 23.7 | 25.7 | 25.8 | 26.4 | 28.2 | 28.1 | 29.2 | 31.1 | 32.8 | 33.9 | 35.5 |
| **Race/ethnicity** | | | | | | | | | | | |
| NH White | 20.7 | 23.5 | 24.7 | 24.6 | 26.5 | 26.1 | 27.7 | 31.0 | 33.6 | 35.1 | 36.4 |
| NH Black | 24.2 | 24.4 | 24.9 | 26.1 | 27.6 | 27.8 | 29.0 | 30.4 | 31.2 | 32.3 | 33.3 |
| Hispanic/Latino | 20.0 | 19.4 | 19.3 | 21.1 | 23.3 | 23.0 | 24.7 | 25.6 | 27.0 | 28.1 | 29.7 |
| NH Asian | 24.4 | 25.6 | 26.6 | 27.8 | 30.0 | 29.5 | 32.4 | 32.7 | 34.3 | 37.1 | 39.2 |
| NH Multiple Races | 25.2 | 25.7 | 25.6 | 27.7 | 28.9 | 29.4 | 29.7 | 30.7 | 31.6 | 32.9 | 34.4 |
| NH AI/AN | 27.5 | 28.0 | 29.8 | 23.3 | 27.3 | 26.3 | 30.4 | 29.5 | 30.2 | 33.6 | 34.6 |
| NH NHOPI | 20.7 | 23.4 | 26.3 | 24.4 | 28.3 | 28.4 | 29.5 | 29.9 | 30.8 | 33.6 | 34.2 |
| NH Other Race | 16.0 | 18.0 | 16.2 | 17.6 | 19.7 | 18.0 | 19.6 | 22.0 | 23.4 | 25.0 | 26.0 |

## Stratified trends and interaction analyses

The overall unstratified population demonstrated a stable and uninterrupted compounding relative rate of increase (Table 3), across the entire period (APC = 4.78%, Davies' test p = 0.411). The annualized interaction models revealed distinct relative dynamics across demographics.

Although the adjusted prevalence was initially higher among males, the relative rate of increase was relatively higher among females (APC=5.6%; 95% CI: 4.7-6.4) than in males (APC=3.8%; 95% CI: 3.4-4.3). The male trend was significantly flatter than that of females (interaction coefficient: -0.0166; $p$ <0.001), demonstrating a progressive narrowing of the initial baseline gap and a shifting sex-based disparity over time.

Children aged 2–5 years experienced a flat, stagnant trend over the entire period (APC=0.5%; 95% CI: -3.0-4.1; p = 0.769). All other ages from age 6 through 80+ years demonstrated robust, highly significant annual relative increases ranging from 4.8% to 7.0% (p-values < 0.001). Using the 20–39 (APC=6.5%) age group as reference, the interaction model confirmed that the 2–5 age bracket expanded at a significantly slower relative rate (p < 0.001). The relative rates of changes for all other age groups were statistically parallel to the 20–39 (all p-values > 0.05), suggesting that the relative acceleration of MetS is a universal life-course phenomenon spared only in early childhood.

The racial/ethnic strata demonstrated distinct relative trajectories with a high-pace relative tier comprising the White (APC=5.47%; 95% CI: 4.60-6.35), Asian (APC: 4.67%), Hispanic/Latino (APC: 4.57%), NHOPI (APC: 4.54%), and Other Race (APC: 4.92%) emerged. These groups tracked along statistically similar trajectories, with none showing a significant difference from Whites (all comparison p-values > 0.05). Conversely, a moderate-pace tier consisting of Black (APC: 3.47%), Non-Hispanic Multiple Races (APC=3.15%), and AI/AN (APC=2.30%) populations experienced significantly slower relative compounding rates of increase compared to the Whites (p-values < 0.01).

Table 3: Stratified Annual Percent Change (APC) and interaction analysis of **MetS** prevalence

| Demographic | Stratum | APC (%) and 95% CI | Baseline p-value | Comparison p-value (vs. reference) |
|---|---|---|---|---|
| **Overall population** | — | **4.78 (4.17-5.39)** | **<0.001** | — |
| **Sex** | Female | 5.6 (4.7-6.4) | <0.001 | Reference |
| | Male | 3.8 (3.4-4.3) | <0.001 | **<0.001** |
| **Age group** | 2–5 | 0.48 (-3.0-4.1) | 0.769 | **<0.001** |
| | 6–11 | 4.8 (3.9-5.7) | <0.001 | 0.121 |
| | 12–19 | 5.5 (4.0-7.1) | <0.001 | 0.339 |
| | 20–39 | 6.5 (5.3-7.8) | <0.001 | Reference |
| | 40–59 | 5.0 (4.3-5.7) | <0.001 | 0.170 |
| | 60–79 | 5.8 (5.0-6.6) | <0.001 | 0.512 |
| | 80+ | 7.0 (6.0-7.9) | <0.001 | 0.705 |
| **Race/ethnicity** | NH White | 5.47 (4.60-6.35) | <0.001 | Reference |
| | NH Black | 3.47 (3.19-3.74) | <0.001 | 0.003 |
| | Hispanic/Latino | 4.57 (3.81-5.33) | <0.001 | 0.164 |
| | NH Asian | 4.67 (4.21-5.13) | <0.001 | 0.217 |
| | NH Multiple races | 3.15 (2.77-3.53) | <0.001 | <0.001 |
| | NH AI/AN | 2.30 (0.42-4.21) | 0.022 | <0.001 |
| | NH NHOPI | 4.54 (3.50-5.58) | <0.001 | 0.151 |
| | NH Other Race | 4.92 (3.60-6.27) | <0.001 | 0.399 |

***Note**: Baseline p-values evaluate whether an individual stratum's slope is significantly different from zero (flat).*
*Comparison p-values are derived from the log-linear interaction term (Year*Demographic component), testing whether that stratum's slope deviates significantly from the designated reference group.*

## Absolute accumulation and systemic breakpoints

Table 4 shows that on an absolute scale, the overall population experienced a significant inflection point in 2020. The population exhibited steady prevalence growth (APPC=0.90; 95% CI: 0.62-1.17; $p < 0.001$) pre-2020, that nearly doubled to an APPC of 1.71 (95% CI: 1.43-1.98; p=0.005) post-2020. **Supplementary Figures 1-4** shows the inflection points visually. Both genders experienced significant post-2020 accelerations, though females exhibited a steeper absolute post-pandemic trajectory (APPC = 1.96) compared to males (APPC = 1.39).

Trend shifts varied by age with older adults (40+) maintaining high absolute growth rates across the entire decade (APPCs > 1.5), which the 2020 pandemic did not significantly alter (all Slope Difference $p > 0.25$). Conversely, younger cohorts experienced trend breakpoints with adolescents (Ages 12–19) demonstrating a statistically flat trajectory prior to 2020 (APPC=0.102, p=0.055),

which accelerated into significant growth post-2020 (APPC=0.88, p<0.001; Slope Difference p<0.001). Young adults (Ages 20–39) mirrored this shock, nearly tripling their growth velocity from 0.70 pre-pandemic to 2.05 post-pandemic (p=0.001).

Across racial and ethnic lines, significant post-2020 accelerations were observed in Whites (p = 0.001), Asians (p=0.041), and Other Race (p=0.011) populations. The greatest shift occurred among AI/AN individuals, whose prevalence trajectory inverted from a flat/negative baseline (APPC=-0.25, p=0.545) to significant growth post-2020 growth of (APPC=1.61, p=0.004; Slope Difference p=0.030). In contrast, Black, Hispanics/Latinos, NH Multiple Races, and NHOPI cohorts maintained steady, significant upward trajectories throughout the decade, but did not exhibit statistically significant slope changes after 2020 (all Slope Difference p > 0.05).

### Sensitivity analysis of alternative breakpoints

Shifting the inflection point confirmed that the 2020 structural break provided the strongest statistical evidence for trend acceleration across the overall cohort and most demographic strata (**Supplementary Table 1**). Results utilizing a 2021 breakpoint closely mirrored the 2020 findings. However, the strength of evidence for structural shifts systematically deteriorated when the knot was shifted to 2022 or 2023. The singular exception was the Asian cohort (**Supplementary Table 1**), which maintained its trend acceleration but demonstrated its most pronounced and highly significant structural break around 2023 (APPC = 2.54; 95% CI, 1.84- 3.25, Slope Difference p=0.006).

Table 4: Annual percentage point change (APPC) trends on the absolute scale

| Demographic | Stratum | Trend segment | APPC [95% CI] | p-value (trend) | p-value (Slope difference) |
|---|---|---|---|---|---|
| Overall | All | 2015–2020 | 0.90 [0.62-1.17] | <0.001 | |
| | | 2020–2025 | 1.71 [1.43-1.98] | <0.001 | 0.0052 |
| Age group | 2-5 | 2015–2020 | -0.03 [-0.09-0.03] | 0.3028 | |
| | | 2020–2025 | 0.04 [-0.02-0.09] | 0.2027 | 0.2006 |
| | 6-11 | 2015–2020 | 0.19 [0.10-0.28] | 0.0015 | |
| | | 2020–2025 | 0.23 [0.14-0.32] | <0.001 | 0.6099 |
| | 12-19 | 2015–2020 | 0.10 [0.00-0.21] | 0.0549 | |
| | | 2020–2025 | 0.88 [0.78-0.99] | <0.001 | <0.001 |
| | 20-39 | 2015–2020 | 0.70 [0.34-1.06] | 0.0021 | |
| | | 2020–2025 | 2.05 [1.69-2.41] | <0.001 | 0.0013 |
| | 40-59 | 2015–2020 | 1.58 [1.01-2.16] | <0.001 | |
| | | 2020–2025 | 2.12 [1.54-2.69] | <0.001 | 0.2641 |
| | 60-79 | 2015–2020 | 2.47 [1.68-3.25] | <0.001 | |
| | | 2020–2025 | 2.48 [1.70-3.27] | <0.001 | 0.9754 |
| | 80+ | 2015–2020 | 2.25 [1.37-3.14] | <0.001 | |
| | | 2020–2025 | 3.07 [2.19-3.95] | <0.001 | 0.2664 |
| Sex | Female | 2015–2020 | 0.95 [0.59-1.32] | <0.001 | |
| | | 2020–2025 | 1.96 [1.60-2.32] | <0.001 | 0.0069 |
| | Male | 2015–2020 | 0.80 [0.57-1.02] | <0.001 | |
| | | 2020–2025 | 1.39 [1.16-1.61] | <0.001 | 0.0101 |
| Race | NH White | 2015–2020 | 0.97 [0.56-1.38] | <0.001 | |
| | | 2020–2025 | 2.04 [1.63-2.45] | <0.001 | 0.0098 |
| | NH Black | 2015–2020 | 0.84 [0.68-1.00] | <0.001 | |
| | | 2020–2025 | 1.09 [0.92-1.25] | <0.001 | 0.0863 |
| | Hispanic/Latino | 2015–2020 | 0.83 [0.48-1.19] | <0.001 | |
| | | 2020–2025 | 1.29 [0.93-1.65] | <0.001 | 0.1367 |
| | NH Asian | 2015–2020 | 1.10 [0.78-1.43] | <0.001 | |
| | | 2020–2025 | 1.72 [1.39-2.05] | <0.001 | 0.0407 |
| | NH Multiple races | 2015–2020 | 0.84 [0.58-1.10] | <0.001 | |
| | | 2020–2025 | 0.97 [0.71-1.23] | <0.001 | 0.5488 |
| | NH AI/AN | 2015–2020 | -0.25 [-1.16-0.66] | 0.5454 | |
| | | 2020–2025 | 1.61 [0.70-2.51] | 0.0035 | 0.0297 |
| | NH NHOPI | 2015–2020 | 1.36 [0.81-1.90] | <0.001 | |
| | | 2020–2025 | 1.08 [0.53-1.63] | 0.0019 | 0.5319 |
| | NH Other Race | 2015–2020 | 0.45 [0.02-0.87] | 0.0406 | |
| | | 2020–2025 | 1.52 [1.10-1.95] | <0.001 | 0.0106 |

*APPC = Annual Percentage Point Change. p-value (trend) evaluate whether a trajectory is significantly different from zero (flat). p-value (Slope Difference) shows whether post-2020 prevalence trajectory diffe from the pre-2020.*
*NH = Non-Hispanic; AI/AN = American Indians/Alaska Natives; NHOPI = Native Hawaiian/other Pacific Islanders*

## Discussion

This study demonstrates the critical utility of deploying large-scale electronic health record (EHR) infrastructure as a surveillance system for monitoring chronic diseases in the occurrence of macro-societal disruptions. By leveraging over 9 million annualized records across an 11-year period, the findings illustrate that routine EHR data can successfully map the structural shocks such as the COVID-19 pandemic on the clinical burden of MetS. Crucially, this analysis established a fundamental methodological imperative for population health. Relying exclusively on relative metric (APC), creates a blind spot that obscures acute shifts in institutional demand. As demonstrated by the divergent post-2020 trajectories across age and racial strata, it is only through the integration of absolute metric (APPC) that public health frameworks can accurately capture the true volumetric expansion of disease and detect when vulnerable populations are structurally insulated from routine care.

The overall age-adjusted prevalence rose by more than 10 percentage points over a decade, with a marked change in trend around the year 2020. This coincided with introduction of behavioral disruptions including reductions in baseline physical activity, altered dietary patterns, and heightened psychosocial stress [20, 21] alongside the of routine healthcare access and potential direct physiological impacts of SARS-CoV-2 on metabolic pathways [22].

## Comparison to national trends

The observation that overall prevalence reached 35.1% in 2025 aligns closely with recent cross-sectional data from the National Health and Nutrition Examination Survey (NHANES), which estimates the unadjusted national adult prevalence to hover between 35.5-41.6% [3]. However, the rapid acceleration observed in this cohort highlights a distinct regional vulnerability. Indiana consistently ranks above the national average for individual cardiometabolic risk factors including obesity, physical inactivity, and type 2 diabetes positioning the region as a critical focal point for the compounding Midwestern metabolic crisis [23, 24]. While national surveillance tools like NHANES provide invaluable intermittent snapshots, their pooled cycles lack the temporal granularity required to detect temporal inflection points.

## Epidemiological perspectives: relative rates versus absolute burden

A central finding of this study is the divergence between the relative and absolute dimensions of MetS prevalence. The population-wide trend demonstrated that MetS advanced at a steady, compounding annual relative rate of increase without a distinct interruption. However, when examined on the absolute scale the overall population experienced a significant inflection around 2020. This isolated a critical epidemiological observation that the pandemic did not merely temporarily suppress healthcare utilization but also acted as a catalyst that accelerated prevalence of MetS trajectories for specific demographic subgroups.

## Age-stratified vulnerability

The trends revealed a uniform compounding relative rate of increase across all ages except the 2–5-year-olds, indicating that the underlying secular momentum of the epidemic was relatively universal. Unlike older adults, whose absolute scale trends remained steady, adolescents and young adults experienced a sharp shift aligned with the COVID-19 disruptions. The abrupt suspension of structured physical activity, the transition to remote learning, and elevated psychosocial stressors severely inflected the historically stable absolute baselines of these youth cohorts.[20, 21] This shift

accelerated a latent public health crisis, unmasking a subclinical vulnerability and permanently advancing the lifetime chronic disease timelines for these ages.

### Asymmetric inflections across racial and ethnic strata

The White, Hispanic/Latino, and Asian populations exhibited steeper year-over-year compounding relative rates of increase compared to Blacks and AI/AN. Similarly, the absolute scale trends for the White and Asian populations experienced accelerations that transitioned into significant steepened post-2020 trajectories unlike those for Blacks and Hispanics/Latinos that did not experience a statistically significant pandemic breakpoint.

This indicates that the overall burden of the Black and Hispanic populations was driven by a steady rate of disease accumulation rather than an acute systemic shock. However, the lack of an acceleration hypothetically associated with the pandemic in these populations does not indicate an absence of risk but rather a prevalence that was already climbing at a high, entrenched velocity prior to 2020 that the pandemic disruption did not alter. This lack of an acute post-2020 surge may also reflect barriers in the post-pandemic healthcare system, preventing these populations from experiencing the same documented diagnostic catch-up observed in the Whites and Asians following the return to routine clinical care [25, 26]. The profound trend inversion among the AI/AN population shifting from a statistically flat baseline to rapid post-2020 growth, further underscores the highly heterogeneous impact of the pandemic across racial and ethnic lines.

### Sensitivity check

The sensitivity analysis reinforced 2020 as the universal systemic shock for the broader population, while isolating a distinct, delayed trajectory for the NH Asian cohort. The identification of a highly significant 2023 breakpoint for this specific population suggests unique post-pandemic healthcare dynamics. This delayed acceleration likely reflects a prolonged reduction in routine care-seeking behaviors during the immediate pandemic years, followed by delayed diagnostic catch-up once standard healthcare utilization fully normalized.

### Methodological strengths and limitations

The primary strength of this study is its utilization of continuous, large-scale EHR data, which unlike cross-sectional surveys, enabled the precise annual tracking of structural inflection points and temporal granularity detection.

However, few limitations warrant consideration. First, because these data are derived from active clinical encounters, the metrics capture documented diagnostic patterns rather than true, asymptomatic population-wide prevalence. Consequently, the acute post-2020 absolute acceleration must be interpreted with caution as it may partially reflect a diagnostic catch-up effect resulting from deferred preventive care and delayed clinical presentations during the initial phases of the pandemic. Second, while regional dataset offers depth, these findings reflect a specific Midwestern cohort and may not fully generalize to populations with different baseline demographic or socioeconomic distributions. Finally, residual confounding remains possible, as EHR data lack standardized, longitudinal metrics for unmeasured lifestyle behaviors, including precise dietary patterns and physical activity levels.

Estimates for smaller racial and ethnic groups - Asians, American Indians and other Native Americans, and Native Hawaiian and other Pacific Islanders should be interpreted cautiously due to small sample sizes.

## Conclusion and Public Health implications

Over the 11-year study period, relative growth in MetS remained steady, but absolute clinical burden accelerated around 2020, particularly among younger age groups. Black and Hispanic populations did not experience a post-2020 surge because their baseline rates were already climbing steadily. To better track clinical demand, public health surveillance should report absolute metrics, such as annual percentage point change (APPC), alongside relative metrics like annual percentage change (APC). Addressing these persistent disparities requires combining clinical interventions including the Diabetes Prevention Program (DPP) [27], nutritional support, and anti-obesity medications[28] with community-based care, such as integrating Community Health Workers (CHWs) into EHR workflows [29, 30].

## Declarations

**Ethics approval**: This study was conducted under the umbrella of Multi-State EHR-Based Network for Disease Surveillance (MENDS) which received exemption from the Human Research Protection Program (HRPP) at Indiana University (Protocol # 2010317218) as Category 4(iii) of the 45 CFR 46 (Revised Common Rule) in accordance with the ethical principles of the Belmont Report.

**Availability of data and materials**: All data generated or analyzed during this study are included in this published article and its supplementary information.

**Competing interests**: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript.

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**Authors' contributions**: MEW conceptualized the original idea, gathered and analyzed the data, wrote the starting draft. BED arranged access to the Institutes Database for the project, acquired the MENDS project funding, provided mentorship, reviewed and added content to the original and subsequent iterations of the manuscript. All authors reviewed, edited and agreed on the final draft, took ownership on AI generated language editing and content in any suggested reference, and agreed on the journal to publish the work.

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