

Childhood Growth Monitoring Overcoming the Limitations of Classic Standards by Big Data Facilities. Basque Country 2026 Transversal Study

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ABSTRACT

Introduction: Classic growth references (WHO, Orbeagozo) may be outdated or poorly adapted to local specificities. Big Data provides a contemporary and efficient alternative for growth monitoring.

Methods: An analysis was conducted on 21,574 BMI records of children and adolescents (aged 0-18.5 years) in the Basque Country. Standard Deviation Scores (SDS) were compared using three references: WHO, Orbeagozo 2011, and Spain 2010.

Results: The WHO reference overestimates the prevalence of obesity (6.1% vs. 2.8% using Orbeagozo) and underestimates thinness (0% vs. 10.4%). High-prevalence clusters were identified at the health center level.

Conclusions: It is necessary to adopt dynamic references based on Big Data to ensure diagnostic accuracy tailored to the current biotype and temporal reality of the population.

Introduction

The evaluation of physical growth and development is arguably the most sensitive indicator of health, nutrition, and well-being in a pediatric population [1]. In daily clinical practice, primary care pediatricians use anthropometry as a fundamental screening tool to early identify endocrinological disorders, underlying chronic diseases, and nutritional deviations that could compromise an individual's biological potential if undetected [2,3]. Historically, this assessment has been based on comparing the patient against standard growth charts. However, the validity of these tools in the context of a hyperconnected society undergoing constant demographic changes is currently being

questioned by the international scientific community [4]. One of the most profound theoretical debates in modern auxology is the distinction between what the population "is" and what it "should be" [5]. The World Health Organization (WHO) growth standards, published in 2006, were designed under the premise of prescribing how children should grow under optimal environmental conditions, regardless of their ethnic or geographical background [6]. While this approach holds global normative value, its systematic application in developed Southern European populations, such as the Basque Country, has revealed notable discrepancies. Previous studies suggest that the use of WHO standards tends to overestimate the prevalence of overweight

and obesity in our environment, while simultaneously “normalizing” statures that could be considered short for the local biotype [7,8].

On the other hand, national references, such as the 2010 Spanish Growth Studies (Carrascosa et al.) and the local tables from the Faustino Orbegozo Foundation (2011), offer a descriptive view of the population [9,10]. Nevertheless, these tools suffer from methodological anachronism. Being closed cross-sectional or longitudinal studies, they represent a “cohort frozen in time” that fails to capture the secular growth trend and rapid changes in body composition driven by contemporary nutritional transitions [11,12]. The traditional methodology for creating growth charts is a process of extraordinary logistical and financial complexity. The selection of representative samples, the technical training of anthropometrists, and the prolonged follow-up of subjects require public resources that can hardly be sustained as frequently as necessary [13,14]. Consequently, clinicians are forced to work with tables that are, at best, 15 years old. During this period, the pediatric population has experienced significant changes due to immigration, shifting sleep habits, digital sedentary lifestyles, and exposure to endocrine disruptors—factors that alter growth patterns and remain uncaptured by classic tables [15]. Over the last decade, the massive digitalization of health systems has opened an unprecedented window of opportunity through Real World Data [16].

In the Basque Health Service (Osakidetza), every Child Health Program check-up generates a digital trace of weight, height, and head circumference stored in the electronic health record. Processing this vast volume of information via Big Data techniques transforms administrative records into high-resolution epidemiological knowledge [17]. Unlike classic studies, population-based Big Data offers an N that approaches the total pediatric population of a region, eliminating selection biases inherent to voluntary sampling [18]. This methodology enables, for the first time, a growth monitoring system that is contemporary, efficient, and locally sensitive, facilitating precision pediatrics down to the health center level [19,20]. Transitioning from a “static paper references” model to a “dynamic digital surveillance” model is not merely a technical upgrade, but an ethical and clinical necessity to ensure that diagnoses of malnutrition—whether by excess or deficit—are based on updated scientific grounds tailored to the social reality of our time. I will now translate and summarize the “Objectives” and “Material and Methods” sections from your document into academic English, ensuring that all the citations remain intact just as you requested.

Objectives

The main purpose of this study is to propose and validate a new paradigm for childhood growth monitoring based on the massive analysis of contemporary population data, comparing its utility against traditional diagnostic models in the pediatric setting of the Basque Country. To achieve this goal, the following specific objectives were established:

- 1. Assessment of Contemporary Nutritional Prevalence:** To determine the current prevalence of obesity and thinness in the pediatric and adolescent population (0-18 years) using a massive Real World Data database from the year 2026, and to analyze its epidemiological distribution to identify vulnerable geographical areas.
- 2. Comparative Analysis of Anthropometric References:** To quantify diagnostic discrepancies in detecting obesity (SDS > 2) and thinness (SDS < -2) when applying three different standards: World Health Organization (WHO), Faustino Orbegozo Foundation (2011), and the 2010 Spanish Growth Studies.
- 3. Validation of Big Data Methodology in Auxology:** To demonstrate the technical and scientific viability of using electronic health records to generate dynamic reference charts, comparing the statistical power and cost-efficiency of a total population sample against limited classic studies.
- 4. Proposal of a New Epidemiological Surveillance Framework:** To lay the groundwork for a “real-time” growth monitoring system and discuss the ethical and professional need to transition toward local, contemporary references to prevent diagnostic errors.

Material and Methods

A descriptive, cross-sectional, population-based study was conducted using Real World Data extracted from the Electronic Health Records (EHR) of the Basque Health Service (Osakidetza) for the year 2026. The database comprised anthropometric records collected during routine Child Health Program check-ups and on-demand consultations. The initial sample included all individuals aged 0 to 18.5 years with at least one recorded weight and height control across the seven active health regions (Araba, Bilbao, Euzkerraldea-Enkarterri, Gipuzkoa Este, Gipuzkoa Oeste, Interior, and Uribe). In accordance with methodological recommendations for the use of Big Data in pediatric health [21], records identified as “Departamento Sanidad” were excluded to avoid administrative duplications. A strict data cleaning protocol was applied to eliminate recording errors: records with biologically implausible Body Mass Index (BMI) values (< 10 kg/m² or > 45 kg/m²) or missing essential variables were discarded. The final cleaned sample consisted of 21,574 subjects, ensuring a statistical power superior to most classic cross-sectional studies conducted nationally [22].

The primary variables studied were weight, height, and BMI. Nutritional status was classified by calculating the Standard Deviation Scores (Z-Scores or SDS) of the BMI using three distinct bibliographic references: the prescriptive international WHO standard (2006/2007), the local historical reference of Orbegozo (2011), and the consensus national reference of the Spanish Growth Studies (2010). Obesity was defined as an SDS > +2 and thinness as an SDS

< -2 across all references. Local Z-Scores were calculated using the mean and standard deviation of the contemporary population sample via spline interpolation techniques to smooth the growth curves by age and sex [23]. Massive data processing was performed using Python 3.x, utilizing Pandas for data manipulation, SciPy for reference curve interpolation, and Matplotlib/Seaborn for visual representation. Descriptive analyses and statistical significance tests (Chi-square, $p < 0.05$) were conducted to compare prevalences. The study was approved by the CEIC of OSI Araba (Expte 2022-058) and adhered to Good Clinical Practice (GCP) standards and the Declaration of Helsinki. Furthermore, an inclusive approach was adopted following the SAGER (Sex and Gender Equity in Research) guidelines, integrating a gender perspective transversally throughout the research design to identify potential biases or disparities. I will now translate and summarize the "Results" section of your manuscript into academic English. As per your instructions, this section has been tailored to focus strictly on the analysis related to Figures 1-3, entirely omitting references to the height and weight comparison charts (the former). All bibliographic citations have been maintained.

Results

The data consolidation process yielded a final cohort of 21,574 subjects. The database cleaning eliminated erroneous administrative records and physiologically implausible values, resulting in a sample with a sex distribution of 51.2% males and 48.8% females, ensuring the absence of gender bias in global inferences. Chronologically, the sample continuously covers the spectrum from the neonatal period up to late adolescence (18.5 years). The distributions of all recorded data are represented as scatter plots (Figure 1) for each of the variables studied. Furthermore, sample processing enabled the reconstruction of cross-sectional growth charts (Basque Country 2026) for the entire cohort across weight, height, and Body Mass Index (BMI). Extreme percentiles (P3-10 and P90-97), representing potential pathological zones, are shaded (Figure 1). Geographically, representativeness is absolute across the Basque territory, covering all seven health regions.

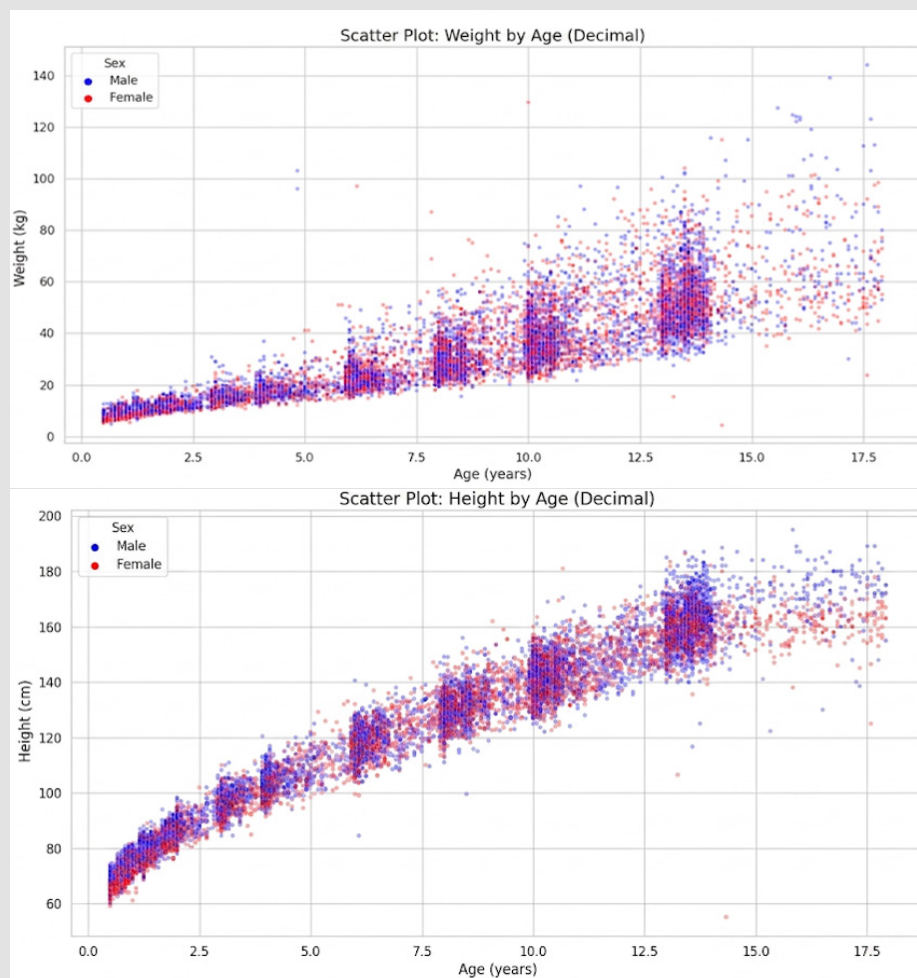


Figure 1: Scatter plot representation of the weight and height variables of the total sample according to age and sex. Boys in blue, girls in red.

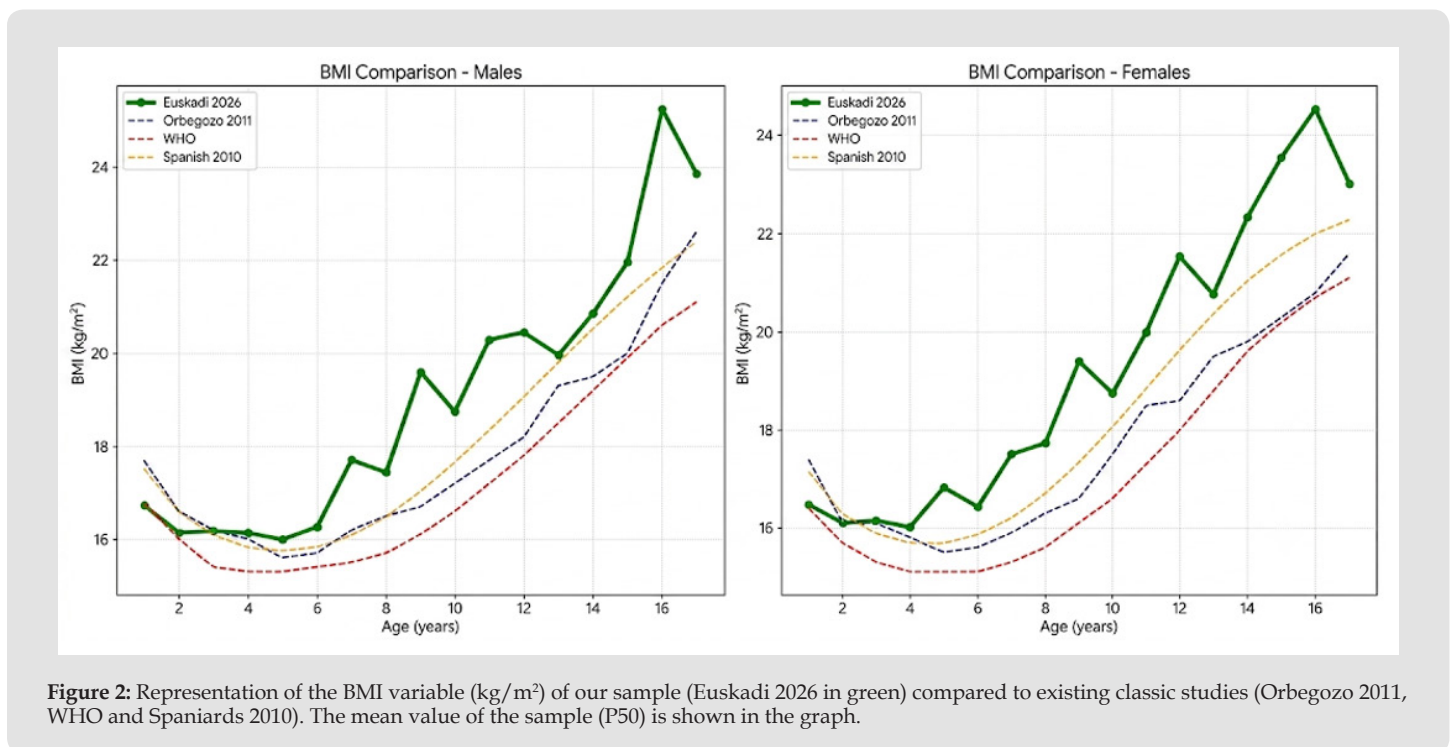
Discrepancies in the Prevalence of Obesity (SDS > +2) The primary finding is the diagnostic variability highly dependent on the chosen reference standard. The application of the WHO standard yields a regional obesity prevalence of 6.1%. However, comparing WHO versus Orbeagozo 2011, while the WHO identifies 767 subjects with obesity, the Orbeagozo reference only classifies 352 under this criterion.

This indicates that 54% of children classified as obese by the WHO would be considered within the normal range (albeit in the high percentiles) under the local Basque standard. A clear geographic gradient is also observed in the territorial analysis of obesity.

Critical Analysis of Thinness and the "Floor Effect" (SDS < -2) The results concerning underweight or thinness present the most significant statistical divergence in the study, revealing a diagnostic annulment phenomenon by international standards. Under the WHO standard, the detected thinness rate is virtually non-existent (0.00% across almost the entire territory), rendering this chart useless as a screening tool for undernutrition or early-stage eating disorders. In stark contrast, the Orbeagozo reference identifies 10.4% of the population within the thinness range. This 10-percentage-point difference reveals that the 3rd percentile of the contemporary Basque population is significantly higher than the WHO's 3rd percentile. The comparative differences for the BMI variable in our population versus the differ-

ent standards are represented in Figure 2. A standout capability of the employed Big Data methodology is the ability to descend from the regional level to the specific health center level. The study detected high-prevalence "clusters" that would remain hidden in a regional average, demonstrating that growth surveillance requires contemporary tools allowing for localized public health interventions—a capacity classic studies lack due to insufficient statistical power at the micro-area level. The differences in the number of cases observed in our study population across health regions and variables, according to the different standards, are represented in Figure 3. A statistically significant number ($p < 0.05$) of cases detected as obesity (BMI > 2 SDS) or thinness (BMI < -2 SDS) fluctuate depending on the applied standard, heavily implying a bias of overestimation or underestimation based on the chosen reference.

Finally, the computational processing time required to calculate Z-scores for the 21,574 subjects and generate comparative tables by region was merely 9.4 seconds. This finding validates the efficiency of Big Data not only as an analytical tool but as a continuous, low-cost epidemiological surveillance system. Aquí tienes la redacción de la Discusión y las Conclusiones en inglés académico, estructurada en párrafos continuos y cohesionados en lugar de viñetas, manteniendo todas tus referencias bibliográficas intactas:



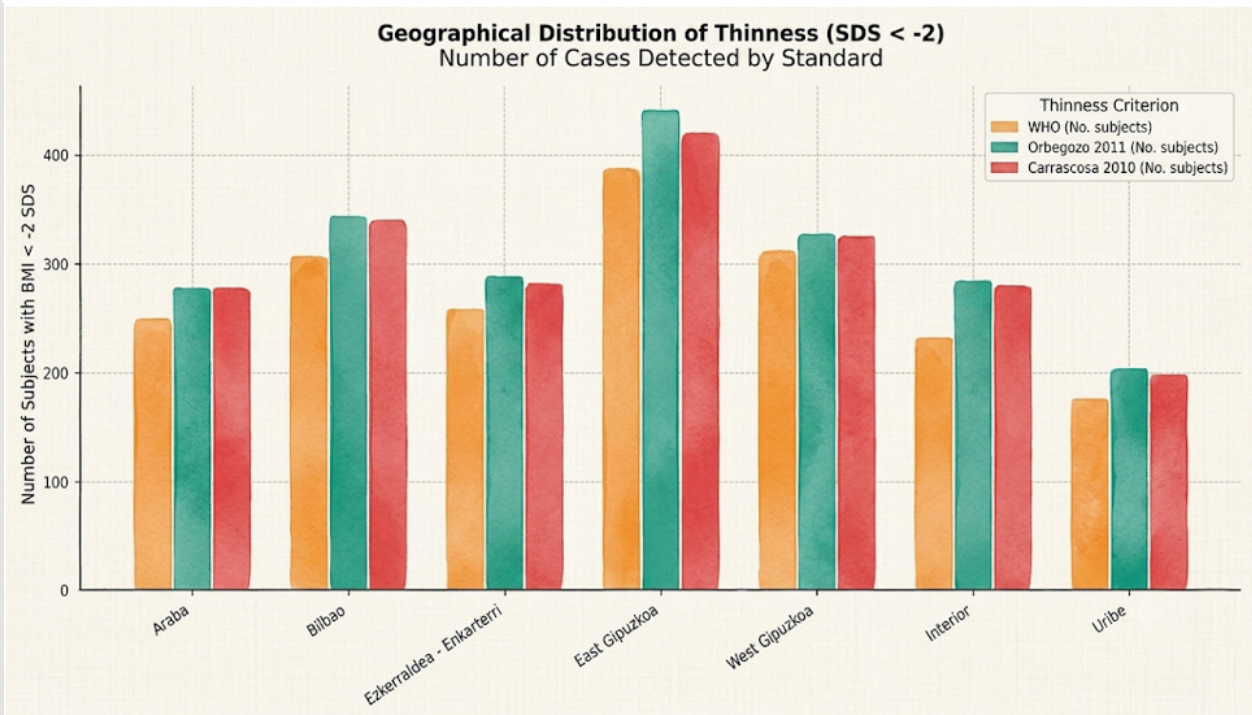
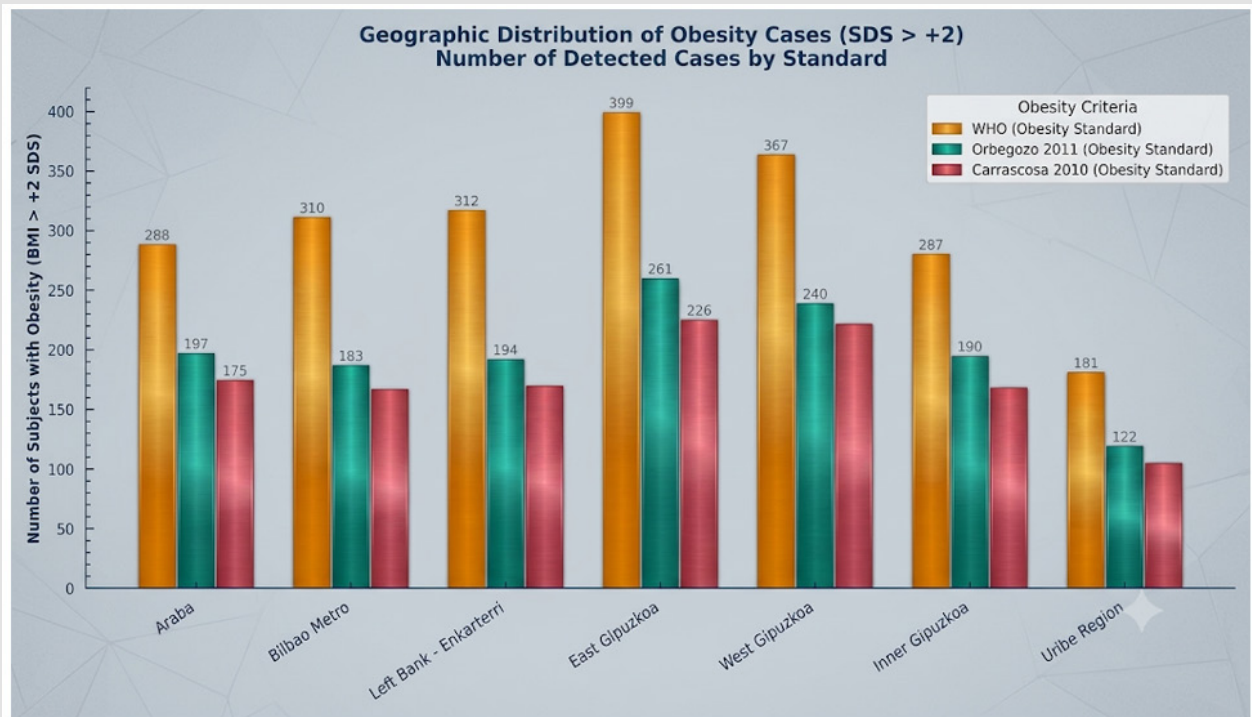


Figure 3: A&B- Representation of the number of individuals in the sample who would be detected with obesity (BMI > 2 SDS) or malnutrition-thinness (BMI<- 2 SDS) according to health districts and chosen standard (WHO, Orbegozo 2011 and Españolas 2010); where the differences in detected cases can be seen.

Discussion

The surveillance of nutritional status in childhood has historically relied on static tools that currently demonstrate methodological exhaustion when faced with the rapid pace of environmental and biological changes. Our results confirm that the use of classic references generates statistical discrepancies and diagnostic biases with direct clinical and healthcare management implications. Specifically, the prevalence of obesity according to the World Health Organization (WHO) (6.1%) is nearly triple that obtained using the Orbeagozo reference (2.8%), highlighting the existing tension between a “prescriptive standard” and a “descriptive reference” [23]. The universal application of a global standard can lead to the pathologization of normal growth in regions with specific biotypes, where the secular trend has shifted the mean BMI independently of pathological adiposity [24,25]. This overestimation of obesity imposes an unnecessary burden on primary care, induces family anxiety, and leads to unjustified dietary interventions [26].

Conversely, the WHO standard’s inability to detect thinness—yielding a rate of 0% compared to 10.4% with the local reference—creates an epidemiological “blind spot” that severely limits the early diagnosis of eating disorders or secondary malnutrition [27]. The massive analysis of Electronic Health Records (Big Data) overcomes the logistical and economic limitations of traditional cross-sectional studies, offering frequent updates at a negligible marginal cost and a sample size that approaches the total population universe [28,29,30]. It is no longer viable to base current clinical practice on data collected fifteen years ago; a transition toward precision pediatrics based on Real World Data is imperative [31,32]. Although there is a risk of inter-observer variability in routine clinical measurements, the sheer magnitude of the sample and the application of strict data cleaning protocols statistically compensate for these potential errors [33-35].

Conclusion

In conclusion, there is a significant incongruence when applying international references, as the WHO standard proves inaccurate for the pediatric population of the Basque Country by overestimating obesity and rendering underweight individuals invisible. Contemporary data demonstrates a greater convergence with the local Orbeagozo 2011 reference, validating that the local biotype remains the safest framework to avoid diagnostic errors. Furthermore, the utilization of massive Electronic Health Record data validates the Big Data model by enabling the analysis of an almost universal population sample with negligible economic costs and immediate processing capabilities. Ultimately, the high granularity of these data allows for the identification of significant variations between health centers, facilitating geographic precision pediatrics and a far more targeted and efficient management of public health resources.

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