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Original Research Article

Is It Possible to Detect Effects of the COVID-19 Pandemic on the Prevalence of Malnutrition-Anorexia Using Big Data Tools in a Pediatric Population?

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ABSTRACT

This research investigates the consequences of the COVID-19 lockdown on pediatric health, with a specific focus on nutritional deficiencies potentially linked to disordered eating. Contemporary Big Data analytical techniques provide a powerful framework for detecting such population-level shifts and exploring their underlying drivers.

Primary Aim: To determine if significant changes occurred in the prevalence of malnutrition, identified by a low body mass index (BMI), among children following confinement during COVID-19. **Methodology:** We conducted a cross-sectional analysis of anonymized data from digital health records. Key metrics—gender, age, weight, and height—were analyzed for a cohort of young people, comparing a pre-pandemic baseline (early 2020) with a post-confinement period (early 2022). Advanced computational models were applied to process these extensive datasets. The analytical strategy utilized the Cole-Green LMS algorithm with penalized likelihood, implemented via RefCurv 0.4.2 software, chosen for its efficacy with large-scale information. Selection of hyperparameters was guided by the Bayesian Information Criterion (BIC). Our specialists in mathematics endorsed this methodological pathway as the most robust for our objectives. Nutritional status was assessed by identifying individuals whose BMI fell more than 2.0 standard deviations below the age-adjusted population mean. **Findings:** The study included 66,975 clinical records from individuals under 16 years, analyzing over 1.2 million distinct data points. Results and comparative visualizations across different geographical districts are presented. A notable rise of 60 instances per 100,000 residents was observed following the pandemic. This increase was not uniform, showing distinct patterns: it was more marked in boys than girls, affected females more in rural settings, and males more in urban centers. **Interpretation:** Leveraging Big Data allows for highly efficient public health surveillance, pinpointing demographic groups that would most benefit from targeted support, thus ensuring optimal use of limited medical resources. Based on these results, proactive screening programs in specific urban zones should concentrate on male adolescents, while in certain rural areas, the focus should shift to female adolescents, who may constitute an under-identified at-risk group.

Keywords—*Big data analytics, Pediatric malnutrition, Nutritional status, COVID-19 impact.*

INTRODUCTION

The body mass index (BMI) serves as a key indicator for evaluating nutritional health in pediatric populations.[1–3] Tracking BMI trajectories is vital for the effective oversight and health promotion of children.[3,4] While scientific literature often emphasizes the escalating issue of childhood obesity[2], another critical dimension of nutritional status—underweight, indicated by a low BMI—demands equal attention.[3] Globally, the predominant reason for a low BMI is undernourishment resulting from food insecurity and poverty[2,3] or chronic illness.

A BMI reading under 2.0 SDS (Standard DeviationS) is generally considered clinically relevant, possibly indicating a pathological condition or at least necessitating a professional evaluation, as it signifies a weight significantly lower than that expected for a child's stature and sex.[2,3]

In affluent societies, however, another significant etiology must be considered: malnutrition secondary to psychological conditions. Therefore, when a child in a developed context presents with low weight-for-height, clinicians must differentiate between organic disease, constitutional lean body habitus, socio-familial nutritional challenges, or psychiatric conditions leading to weight loss, such as anorexia nervosa or restrictive-type bulimia.[2,3]

Anorexia nervosa ranks among the most lethal psychiatric diagnoses.[5] It is characterized by a pervasive fear of weight gain and a profoundly distorted body image, driving intense dietary restriction and weight loss.[5]

Adult prevalence of anorexia nervosa is around 0.6%, with a rising incidence noted in teenage cohorts.[6] This disorder typically emerges in females during early-to-mid adolescence, with higher incidence rates observed in Caucasian demographics and those from higher socioeconomic strata.[7,8]

The mean age of onset is approximately 12.3 years.[7] Epidemiological data from our national context are consistent with these global trends. A consistent finding across multiple investigations is that the public health measures enacted during the COVID-19 crisis[8]—including social distancing, school shutdowns, and increased digital device usage—correlated with a deterioration in youth mental health.

The magnitude of this effect is substantial; reports suggest a 25% to 27% surge in the prevalence of anxiety and depressive disorders post-pandemic.[9] Furthermore, the post-COVID era has witnessed a rise in case numbers, hospital admissions, and a trend toward younger age at presentation for anorexia nervosa, with current prevalence estimates reaching 4% for females and 0.3% for males.[9]

Compounding these issues, the pandemic has intensified systemic weaknesses in healthcare and widened economic disparities, disproportionately impacting teenagers and young adults.[8–10]

Beyond being a potential sign of organic pathology or a nonpathological variant, a lean physique can also indicate a susceptibility to developing an eating disorder. Risk factors associated with these conditions include high academic achievement, familial history of eating disorders, an excessive focus on muscularity (vigorexia), domestic conflict, and difficulties associated with pubertal development.[8–10] Crucially, being underweight can also be a marker of a family's experience of social or financial marginalization.

According to a UNICEF analysis[11], Spain faces a child poverty and social exclusion risk rate as high as 28%. This statistic has profound potential implications for the dietary well-being of affected minors.

Modern healthcare systems' digital archives accumulate a multitude of clinical variables during standard care, encompassing both anthropometric and sociodemographic information.

Sophisticated analytical approaches, like machine learning, allow researchers to harness these data from enormous sample sizes in a largely automated manner, generating insights with considerable statistical validity.

Although international research and cross-national analyses on this topic exist[10], a gap remains: no studies have specifically examined the landscape of under-nutrition in the child and adolescent demographic within our local and regional context. Moreover, the application of innovative Big Data methodologies for such an inquiry has not been previously documented.

GOALS

Primary Goal: To characterize the prevalence of malnutrition, operationalized as a low BMI, within a pediatric population in Álava, Spain, by employing a Big Data framework at two separate time points: prior to and following the revocation of COVID-19 social restriction policies.

Secondary Aims: To investigate potential associations between malnutrition prevalence and geographic location, district-level average income, and the proportion of immigrant residents.

MATERIAL AND METHODS

Study Design: A cross-sectional, population-level analysis was performed.

Cohort: All patients under 18 years of age enrolled in the OSAKIDETZA public health service of the Basque Country, who had both weight and height measurements documented in the centralized OSABIDE GLOBAL electronic health record system for the Álava region.

Eligibility:

- Male and female individuals
- Age range: 0 to 18 years
- Official registration or declared residence within the catchment area

Exclusion:

- Missing or incomplete essential data in the GLOBAL database

Contextual Data:

Official and reliable statistics on district-level median income, unemployment, and immigration prevalence were sourced from the Basque Statistics Institute (EUSTAT). Accessible via: https://www.eustat.eus/bankupx/pxweb/es/DB/-/PX_010154_cepv1_ep06b.px/table/tableViewLayout1/ (Accessed 08/29/2022).

Enrolling the complete registered pediatric cohort rendered a preliminary sample size calculation redundant. Initial data capture occurred from January 1 to March 30, 2020. A subsequent identical data extraction was conducted from January 1 to March 30, 2022.

Measured Parameters

- Primary measures:
- Body weight (Kilograms)
- Stature (Centimeters)
- Sex (Male, Female)
- Chronological age (Years and months)
- Date of clinical assessment
- Residential location—coded by district/neighborhood
- Local unemployment rate and per capita income

Analytical Approach

Our procedure was grounded in the Dirichlet process (DP) theory. This project embraced a Bayesian nonparametric strategy to construct Gaussian mixture models (GMM). Specifically, we employed DP Gaussian mixture models (DPGMM). For population-level inferences, we utilized hierarchical DP Gaussian mixture models (HDP-GMM).[12] This generated clustering outcomes that reveal somatometric commonalities and divergences within the population, based on physical metrics and residential district[13], integrating recent computational advances tailored for databases with profiles akin to ours.[14–16] BMI was computed as weight in kilograms divided by height in meters squared (kg/m^2). These values were benchmarked against established Spanish reference means and SDS.[4] The case definition for low weight was set at below 2.0 SDS compared to age- and sex-specific normative data.[4]

Our consortium of data scientists evaluated multiple analytical frameworks, ultimately selecting the HDPGMM because of the dataset's magnitude and the team's proven proficiency with such techniques (see the team's prior high-impact work), deeming it the superior instrument for this investigation.

The analysis involved comparative assessments using a paradigm previously validated by Diez et al.[17]: the hierarchical DPGMM, applied to contrast our sample against national reference curves from the 2010 Spanish growth study.

Statistical significance was determined at $p < 0.05$. In line with the model's constraints, only clusters containing

a minimum of 20 subjects with full data were included in the comparative analysis.

RESULTS

The final dataset comprised information from 67,270 young individuals. The aggregate count of examined parameters (some disclosed in this report, others withheld) totals 1,749,020 data cells. Subsequent tables detail findings categorized by sex, age bracket, and BMI, alongside other relevant factors.

Official demographic statistics (National Institute of Statistics, EUSTAT) reported a population of 338,765 individuals in the province of Álava during the analysis timeframe.

The region is administratively partitioned into seven major districts, incorporating the city of Vitoria-Gasteiz. As the Basque capital and primary urban hub, Vitoria-Gasteiz accounts for over 255,000 residents.

The financial well-being of children is intrinsically tied to household earnings. The median household income for the Basque Country stood at €47,005 in 2021. Figure 1 represents the combined gross income of all cohabiting family members, including children. Pronounced economic gradients exist across different districts (EUSTAT source), with several municipalities in Álava registering the most modest average incomes regionally.

Regional unemployment was recorded at 7.5%, significantly lower than the national Spanish average. Disparities are evident across districts (EUSTAT source), with certain localities in Álava and Vizcaya experiencing the highest joblessness levels.

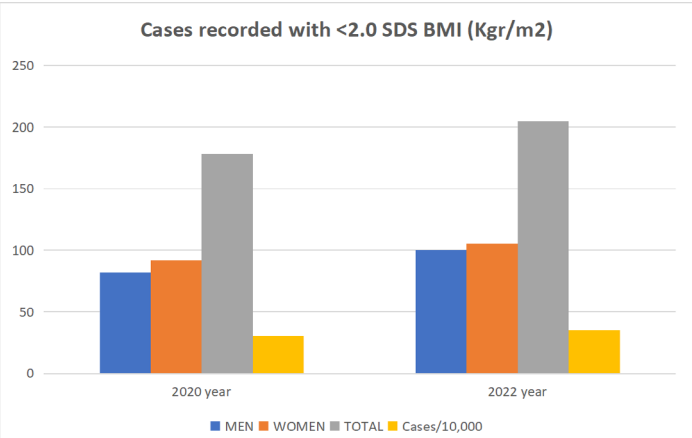

FIGURE 1. Cases with < 2 SDS BMI recorded between 2020 to 2022. Sex differences.

Concerning foreign-born residents, the average for the Basque Country is 13%. However, Vitoria-Gasteiz stands out with one of the highest proportions nationally, at 15%. Specific city districts exceed 18%, and some towns surpass 20%.

Accessible at: https://www.vitoria-gasteiz.org/http/wb021/contenidosEstaticos/adjuntos/es/36/18/3618.pdf. Dec. 2024, and the EUSTAT portal https://www.eustat.eus/estadisticas/tema_131/opt_0/tipo_1/ti_actividad-ocupacion-y-paro/temas.html and https://www.eustat.eus/elementos/ele0000200/migraciones-de-la-ca-de-euskadi-por-ambitos-territoriales-segun-clase-de-migracion-y-sexo/tbl0000255_c.html Dec. 2024.

During the initial 2020 quarter (pre-pandemic), 178 minors under 16 (83 males, 92 females) were identified with a BMI below the 2.0 SDS threshold. This count corresponds to 0.26% of the analyzed sample.

This incidence translated to 30 cases per 100,000 population in 2020.

In the first quarter of 2022 (post-confinement), 205 individuals under 16 (100 males, 105 females) met the same low BMI criterion. Figure 2 represents 0.30% of the total studied cohort.

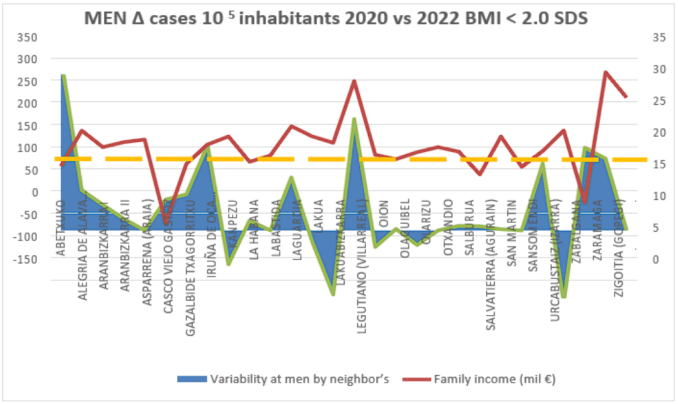

FIGURE 2. Relationship in MEN between changes number of cases and family incomes in different neighbors.

This incidence translated to 35 cases per 100,000 population in 2022.

Statistical analysis confirmed significant differences between the two time intervals and between genders ($p < 0.05$), reflecting a net increase of 27 children, or an additional five cases per 100,000 inhabitants.

Visual 1. Data presentation for BMI (kg/m^2) stratified by sex. The reference population is the normative median (P50) from the Carrascosa study. The graph displays the proportion of the cohort with a BMI falling more than 2.0 standard deviations below their age-specific mean for both observational windows, 2020 versus 2022.

Numerical outcomes are itemized in Tables 1 and 2. Consistent with the clustering protocol, districts reporting fewer than 20 valid cases during the analysis were excluded from the final district-level breakdown.

TABLE 1. Data for men, showing district-level data for 2020 and 2022, percentage values, and the variation between periods.

Men 2020 DISTRICT	Men 2022		DIFFERENCES
	%		% variation
ABETXUKO	0.00	3.90	3.90
ALEGRIA OF ALAVA (DULANTZI)	1.32	2.22	0.91
ARABIZKARRA I	5.34	5.92	0.58
ARABIZKARRA II	1.30	1.56	0.26
ASPARRENA (ARAIA)	4.00	4.00	0.00
OLD TOWN GASTEIZ	1.58	2.27	0.69
GAZALBIDE TXAGORRITXU	1.73	2.54	0.81
IRUÑA DE OCA (NANCLARES)	2.63	4.55	1.91
KANPEZU	4.76	4.00	−0.76
HABANA	2.48	2.70	0.22
LABASTIDA	0.00	0.00	0.00
LAGUARDIA	0.00	1.19	1.19
LAKUA	1.59	1.33	−0.26
LAKUABIZKARRA	2.67	1.23	−1.44
LEGUTIANO (VILLARREAL)	0.00	2.50	2.50
OION	0.99	0.62	−0.37
OLAGUIBEL	1.47	1.50	0.03
OLARIZU	1.49	1.16	−0.33
OTXANDIO	0.00	0.00	0.00
SALBURUA	1.28	1.38	0.10
SALVATIERRA (AGURAIN)	3.75	3.85	0.10
Saint Martin	1.49	1.52	0.03
SANSOMENDI	0.00	0.00	0.00
Urcabustaiz (Izarra)	0.00	1.50	1.50
ZABALGANA	2.89	1.26	−1.63
ZARAMAGA	1.27	3.13	1.86
ZIGOITIA (GOPEGI)	0.00	1.61	1.61
Zuya (Murgia)	0.00	0.00	0.00
TOTAL	**1.57**	**2.05**	0.48

Note: Red numbers indicate negative variation.

TABLE 2. Data for women, showing district-level data for 2020 and 2022, percentage values, and the variation between periods.

DISTRICT	%	%	% variation
ABETXUKO	1.45	1.23	−0.21
ALEGRIA OF ALAVA (DULANTZI)	2.86	2.50	−0.36
ARABIZKARRA I	0.80	2.01	1.21
ARABIZKARRA II	0.76	1.95	1.19
ASPARRENA (ARAIA)	5.00	5.50	0.50
OLD TOWN GASTEIZ	3.90	1.82	−2.07
GAZALBIDE TXAGORRITXU	2.40	2.80	0.40
IRUÑA DE OCA (NANCLARES)	0.00	0.54	0.54
HAVANA	1.04	1.00	−0.04
LABASTIDA	1.28	1.20	−0.08
LAGUARDIA	0.00	1.52	1.52
LAKUA	2.81	1.37	−1.44
LAKUABIZKARRA	2.23	2.20	−0.03
LEGUTIANO (VILLARREAL)	0.00	0.10	0.10
OION	2.25	2.03	−0.22
OLAGUIBEL	3.18	1.37	−1.81
OLARIZU	2.59	3.57	0.98
OTXANDIO	2.35	4.35	2.00
SALBURUA	1.45	1.32	−0.13
SALVATIERRA (AGURAIN)	3.85	3.55	−0.30
Saint Martin	1.64	1.29	−0.35
SANSOMENDI	4.55	4.80	0.25
Urcabustaiz (Izarra)	0.00	0.10	0.10
ZABALGANA	1.77	1.59	−0.19
ZARAMAGA	2.25	1.93	−0.32
ZIGOITIA (GOPEGI)	1.00	2.78	1.78
Zuya (Murgia)	2.17	2.20	0.03

Note: Red numbers indicate negative variation.

Tables 1 and 2 for men and women would be inserted here, showing district-level data for 2020 and 2022, percentage values, and the variation between periods.

Reviewing case distribution reveals an overall upward trend, largely attributable to the male demographic (4 extra cases/100,000). The female cohort contributed a smaller increment (1 additional case/100,000).

Distinct geographical patterns emerged. A widespread increase was evident among boys across most districts,

while girls exhibited a more variable and less uniform distribution.

After independent examination of BMI and income data for each district, we identified those geographical units demonstrating the most substantial relative change in low BMI case numbers between 2020 and 2022, using national reference standards.[4]

Figures 2 and 3, show the relationship in man and woman between changes in case numbers with < 2 SDS BMI and family incomes in different neighbors in our territory.

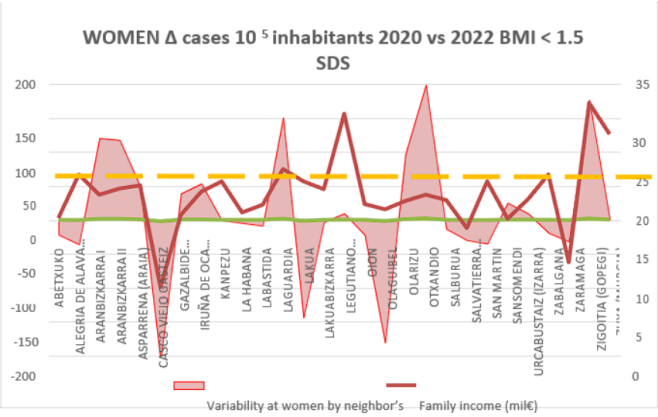

FIGURE 3. Relationship in WOMEN between changes number of cases and family incomes in different neighbors.

For the male population, 2022 witnessed 17 more total cases than 2020. This elevates the proportion from 1.57% to 2.02% of the male sample, denoting a 0.48% absolute and a 28.66% relative surge. This rise was not geographically uniform. Districts such as Abetxuko, Alegria, Gazalbide, Legutiano, Zaramaga, and Zigoitia reported increases markedly above the mean. Most, though not all (e.g., Zaramaga, Abetxuko), are situated in zones with above-average income. Conversely, other areas like Kanpezu, Lakua, and Zabalgana saw a reduction in identified cases. These interdistrict variations are statistically significant ($p < 0.05$).

The female cohort displayed a disparate geographical pattern. A total of 12 new cases appeared in 2022 compared to 2020. This shifted the prevalence from 1.98% to 2.10%, a minor 0.12% absolute and a 6.06% relative growth. This subtle overall increase masks considerable local variation. Significant upticks were recorded in districts including Aramizkarra I and II, La Guardia, Olarizu, Otxandio, Zigoitia, and Zuya. These are largely rural localities with incomes near the regional median, except for Zigoitia, which is a high-income area. Meanwhile, districts like Casco Viejo, Olaguibel, and Lakua experienced declining numbers; the first two are low-income zones. These territorial discrepancies are significant ($p < 0.05$).

DISCUSSION AND CONCLUSION

The capacity for epidemiological inquiry using Big Data is growing exponentially, creating new avenues for health intervention strategies. Machine learning, validated across diverse fields[14–16] for interpreting complex real-world data, is positioned as a transformative asset.

Pediatric physical development metrics[17], as a barometer of general health, and the specific challenge of eating pathologies represent ideal candidates for investigation via these sophisticated computational tools.[18–19]

Prior scholarship has detailed the multifaceted impact of the COVID-19 crisis[20,21], frequently citing the effects of lockdowns, diminished social contact, and increased screen time.

The pandemic period correlated not only with a higher incidence of eating disorders[21] but also with greater acuity, including elevated risks for medical instability, self-harm, and hospital admission.[22]

Other implicated factors encompass family socioeconomic position, household income[23], and the psychological strain of parental job loss.[8,9,11]

UNICEF's metric for child poverty risk uses a threshold of 60% of the national median equivalized household income, adjusted for family structure.[11]

Our investigation incorporated these elements, analyzing accessible district-level variables like average income and immigrant concentration in relation to low BMI. Immigration rate often correlates with larger family size, lower mean income, and higher unemployment.

This study confirms a post-pandemic rise in low BMI cases among youth in both sexes. The methodological design does not permit differentiation between cases stemming from clinical eating disorders, other medical conditions, or socioeconomic deprivation.

Evidence suggests that urban youth may be more vulnerable to mental health difficulties[24,25], potentially because of heightened exposure to pandemic-related biopsychosocial stressors like financial hardship, reduced service access, and limited social interaction, fostering anxiety and depression[26–28], alongside increased risks of familial conflict and violence.[29–32]

Initially, pediatric presentations were dominated by anxiety disorders[33–35], likely fueled by fears of infection and bereavement. Prolonged isolation, however, is strongly linked to the subsequent emergence of depression, social anxiety, self-injurious behaviors, suicidal thoughts, and eating disorders.[24,36–39]

Our research, covering both urban and rural settings, indicates that the male increase was more frequent in urban, often more affluent areas. For females, the rise was most prominent in rural communities and one affluent urban zone. This aligns with literature suggesting boys were more affected in urban, sometimes lower-income neighborhoods, whereas girls were more impacted in rural settings.[26,28,30–32] This divergence may reflect gendered social dynamics and support structures within different environmental contexts.

Healthcare budgets are constrained, complicating decisions about where to direct intervention programs or active screening for nutritional risk. Big Data provides a rapid, cost-efficient mechanism to gain a realistic overview of population health, informing strategic resource investment.[15–17]

Our analysis confirms tangible malnutrition risk within our community, with certain areas showing nearly 4% of all children affected.

This necessitates serious consideration of both the methodological framework[39] and the social determinants of health in our region.

The results further suggest that a child's residential environment influences nutritional status.[8,9,19,20] The interplay of income, food quality/access, opportunities for extracurricular and physical activities[22], and the general milieu of development appears to affect vulnerability to malnutrition critically.

In economically disadvantaged areas[11], child poverty becomes a tangible threat. Children from vulnerable households are more reliant on external support like school meals, charitable aid, and social services.[11] They also typically have less access to enriching recreational, athletic, and cultural pursuits, all factors that can compromise nutritional health.

Child poverty in Spain unequivocally impacts multiple life domains, from educational attainment and health outcomes to overall welfare.

Our analysis enables specific targeting: for boys, screening should emphasize urban neighborhoods with lower incomes and specific higher-income rural towns. The focus for girls is different. The data also reveal an asymmetrical increase, with males experiencing a more pronounced rise than females from 2020 to 2022.

We suggest that public health authorities enhance monitoring of these variables and their sociodemographic correlates, as a low BMI can be a common endpoint of diverse pathways: true food poverty, organic illness, or an eating disorder; but understanding how to intervene effectively against malnutrition risk[23] not only reduces associated mortality but also curtails resource-intensive hospital and emergency care. Big Data utilization is, and will remain, a cornerstone of modern public health[29] for evidence-based policy, offering a tangible opportunity to refine everyday clinical practice.

Finally, we notice as biases and limitations of the study that, a key limitation involves the use of routine clinical data, not originally collected for research. As noted in literature, this can introduce measurement or recording inaccuracies.[3] The study's design permits its regular repetition, facilitating ongoing monitoring of progress within various population subgroups.

AUTHOR CONTRIBUTIONS

Conceptualization, I.D.L. and S.M.M.; Methodology, I.D.L.; Software, I.D.L. and G.S.M.; Validation, all; Formal Analysis, G.S.M.; Investigation, I.D.L.; Resources, G.S.M.; Writing–Original Draft Preparation, all.; Writing–Review & Editing, all; Visualization, all; Supervision, I.D.L.; Project Administration, I.D.L.; Funding Acquisition, I.Z.M. and A.G.

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DATA AVAILABILITY STATEMENT

Official and reliable statistics on district-level median income, unemployment, and immigration prevalence were sourced from the Basque Statistics Institute (EUSTAT). Accessible via: https://www.eustat.eus/bankupx/pxweb/es/DB/-/PX_010154_cepv1_ep06b.px/table/tableViewLayout1/ (Accessed 08/29/2022).

Complete registered pediatric are from official clinical datas -electronic clinical history.

CONFLICTS OF INTEREST

The authors declare they have no competing interests.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This research adhered to the ethical principles of the Declaration of Helsinki (2013, Fortaleza), the Council of Europe's Oviedo Convention (1997), and national regulations on biomedical research and data protection (Law 14/2007). Ethical approval was granted by the Ethics Committee of OSI Araba (CEIC) on 03/24/2023 (Registration Number: 2022-058). Informed consent was not required as only anonymized, aggregated epidemiological data were used.

CONSENT FOR PUBLICATION

Not applicable.

FURTHER DISCLOSURE

Not applicable.

REFERENCES

1. WHO referenced data. Growth reference data from 5–19 years. Available online:https://www.who.int/tools/growth-reference-data-for-5to19-years.
2. Mendon, P., Witsch, M., Becker, M., et al. Facilitating comprehensive child health monitoring within REDCap—an open-source code for real-time Z-score assessments. *BMC Med Res Methodol*. 2024;24(1):298. https://doi.org/10.1186/s12874-024-02405-0.
3. Heude, B., Scherdel, P., Werner, A., et al. A big-data approach to producing descriptive anthropometric references: a feasibility and validation study of pediatric growth charts. *Lancet Digit Health*. 2019;1(8):e413–e423. https://doi.org/10.1016/S2589-7500(19)30149-9.
4. Carrascosa, L.A., Fernández García, J.M., Fernández Ramos, C., et al. Spanish cross-sectional growth study 2008. Part II: height, weight and body mass index values from birth to adult height. *An Pediatr*. 2008;68(6):552–569. https://doi.org/10.1157/13123287.
5. Morales L. M. J. Anorexia nervosa in the pediatric population. *Med. leg. Costa Rica*. 2019;36(2):46–55. https://www.scielo.sa.cr/scielo.php?script=sci_arttext&pid=S1409-00152019000200046.
6. van Eeden, A.E., van Hoeken, D., Hoek, H.W. Incidence, prevalence and mortality of anorexia nervosa and bulimia nervosa. *Curr Opinion Psychiatry*. 2021;34(6):515–524. https://doi.org/10.1097/YCO.0000000000000739.
7. Silén, Y., Keski-Rahkonen, A. Worldwide prevalence of DSM-5 eating disorders among young people. *Curr Opinion Psychiatry*. 2022;35(6):362–371. https://doi.org/10.1097/YCO.0000000000000818.
8. Collantoni, E., Natali, L., Meregalli, V., et al. Decoding the impact of the Covid-19 pandemic on anorexia nervosa psychopathology: A network comparison of pre- and post-pandemic onset. *Psychiatry Res*. 2025;384:116493. https://doi.org/10.1016/j.psychres.2025.116493.

9. Silliman Cohen R.I., Bosk E.A. Vulnerable youth and the COVID-19 pandemic. *Pediatrics*. 2020;146(1):e20201306. https://doi.org/10.1542/peds.2020-1306.
10. Child poverty report in Spain. UNICEF Report 2023. Available online: https://www.unicef.es/causas/pobreza-infantil.
11. Rasmussen, C.E. The infinite Gaussian mixture model. Proceedings of the Advances in neural information processing systems 12. Kongens Lyngby, Denmark, 2000; Solla, S.A., Leen, T.K, eds. MIT Press: Cambridge, USA, 2000.
12. Teh, Y.W., Jordan, M.I. Hierarchical Bayesian nonparametric models with applications. *In Bayesian nonparametrics*. Hjort; N.L., Holmes, C., eds. Cambridge University Press: Cambridge, UK; 2010; pp. 158–207. https://doi.org/10.1017/CBO9780511802478.006.
13. Van der Maaten, L., Hinton, G. Visualizing data using t-SNE. *J Mach Learn Res*. 2008;9(86):2579–2605. https://www.jmlr.org/papers/v9/vandermaaten08a.html.
14. Kruskal, J.B. Non metric multidimensional scaling: a numerical method. *Psychometrika*. 29(2):115–129. https://doi.org/10.1007/BF02289694.
15. Gilholm, P., Mengersen, K., and Thompson, H. Identifying latent subgroups of children with developmental delay using Bayesian sequential updating and Dirichlet process mixture modeling. *PloS one*. 2020;15(6):e0233542. https://doi.org/10.1371/journal.pone.0233542.
16. Díez-López, I., Maeso-Mendez, S., Sánchez-Merino, G. Was the COVID-19 pandemic and home confinement responsible for a childhood obesity pandemic? responses from big data. *Endocrinol Metab Int J*. 2024;12(3):83–90. https://doi.org/10.15406/emij.2024.12.00353.
17. Ahrens, W., Moreno. L.A., Pigeot, I. Childhood obesity: prevalence worldwide. *In: Epidemiology of Obesity in Children and Adolescents*. Moreno L.A., Pigeot, I., eds. Springer Nature: London, UK; 2011. pp. 219–235. https://doi.org/10.1007/978-1-4419-6039-9_13.
18. Umekar, S., Joshi, A. Obesity and preventive intervention among children: a narrative review.*Cureus*, 2024;16(2):e54520. https://doi.org/10.7759/cureus.54520.
19. Boltri, M., Brusa, F., Apicella, E., et al. Short- and long-term effects of Covid-19 pandemic on health care system for individuals with eating disorders. *Front Psychiatry*. 2024;15:1360529. https://doi.org/10.3389/fpsyt.2024.1360529.
20. Dalle, G.R., Chimini, M., Cattaneo, G., et al. Intensive cognitive behavioral therapy for adolescents with anorexia nervosa outcomes before, during and after the COVID-19 crisis. *Nutrients*, 2024;16(10):1411. https://doi.org/10.3390/nu16101411.
21. Winston, A.P., Taylor, M.J., Himmerich, H., et al. Medical morbidity and risk of general hospital admission associated with concurrent anorexia nervosa and COVID-19: an observational study. *Int J Eat Disord*. 2023;56(1):282–287. https://doi.org/10.1002/eat.23851. Epub 2022 Nov 14.
22. Schlissel, A.C., Richmond, T.K., Eliasziw, M., et al. Anorexia nervosa and the COVID-19 pandemic among young people: a scoping review. *J Eat Disord*. 2023;11(1):122. https://doi.org/10.1186/s40337-023-00843-7.
23. Delisle, H., Faber, M., Revault, P. Evidence-based strategies needed to combat malnutrition in Sub-Saharan countries facing different stages of nutrition transition. *Public Health Nutr*. 2021;24(12):3577–3580. https://doi.org/10.1017/S1368980021001221.
24. Del Castillo, P., Velasco, P. Child and adolescent mental health and the Covid-19 pandemic in Spain: issues and challenges. *JCACAP*. 2020;.37:30–44. https://doi.org/10.3390/healthcare11050765 .
25. Deolmi, M., Pisani, F. Psychological and psychiatric impact of COVID-19 pandemic among children and adolescents. *Acta Biomedica*. 2020;91(4):e2020149. https://doi.org/10.23750/abm.v91i4.10870.
26. Duan, L., Shao, X., Wang, Y., et al. An investigation of mental health status of children and adolescents in china during the outbreak of COVID-19.*J Affect Disord*. 2020;275:112–118. https://doi.org/10.1016/j.jad.2020.06.029.
27. Ford, T., John, A, Gunnell, D. Mental health of children and young people during pandemic. *BMJ*. 2021;372:n614. https://doi.org/10.1136/bmj.n614.
28. Galiano, M., Prado, R., Mustelier, R. Mental health in childhood and adolescence during the COVID-19 pandemic. *Rev Cubana Pediatr*. 2020; 92:e1342.
29. Golberstein, E., Wen, H., Miller, B. Coronavirus disease 2019 (COVID-19) and mental health for children and adolescents. *JAMA Pediatrics*. 2020. 174:819–820. https://doi.org/10.1001/jamapediatrics.2020.1456.
30. Isumi, A., Doi, S., Yamaoka, Y., et al. Do suicide rates in children and adolescents change during school closure in Japan? The acute effect of the first wave of COVID-19 pandemic on child and adolescent mental health. *Child Abuse and Neglect*. 2020;110: 104680. https://doi.org/10.1016/j.chiabu.2020.104680.
31. Jones, E.A.K., Mitra, A.K., Bhuiyan, A.R. Impact of COVID-19 on mental health in adolescents: a systematic review. *IJERPH*. 2021;18(5):2470. https://doi.org/10.3390/ijerph18052470.

32. Lee, J. Mental health effects of school closures during COVID-19. *Lancet Child Adolesc Health*. 2020;4(6):421. https://doi.org/10.1016/S2352-4642(20)30109-7.

33. Leeb, R., Bitsko, R., Radhakrishnan, L., et al. Mental health-related emergency department visits among children aged <18 years during the COVID-19 pandemic-United States, January 1–October 17, 2020. *MMWR Morb Mortal Wkly Rep*. 2020. 69(45):1675–1680. https://doi.org/10.15585/mmwr.mm6945a3.

34. Loades, M.E., Chatburn, E., Higson-Sweeney, N., et al. Rapid Systematic Review: The Impact of Social Isolation and Loneliness on the Mental Health of Children and Adolescents in the Context of COVID-19. *J Am Acad Child Adolesc Psychiatry*. 2020. 59(11):1218–1239. https://doi.org/10.1016/j.jaac.2020.05.009.

35. Luijten, M.A.J., Van Muilekom, M.M., Teela, L., et al. The impact of lockdown during the COVID-19 pandemic on mental and social health of children and adolescents. *Qual Life Res*. 2021;30(10):2795–2804. https://doi.org/10.1007/s11136-021-02861-x.

36. Ma, L., Mazidi, M., Li, K., et al. Prevalence of mental health problems among children and adolescents during the COVID-19 pandemic: a systematic review and meta-analysis. *J Affect Disord*. 2021;293:78–89. https://doi.org/10.1016/j.jad.2021.06.021.

37. Magson, N.R., Freeman, J.Y.A., Rapee, R.M., et al. Risk and protective factors for prospective changes in adolescent mental health during the COVID-19 pandemic. *J Youth Adolesc*. 2021;50(1):44–57. https://doi.org/10.1007/s10964-020-01332-9.

38. Meade, J. Mental health effects of the COVID-19 pandemic on children and adolescents: a review of the current research. *Pediatr Clin North m*. 2021;68(5):945–959. https://doi.org/10.1016/j.pcl.2021.05.003.

39. Wesson, P., Hswen, Y., Valdes, G., et al. Risks and opportunities to ensure equity in the application of big data research in public health. *Annu Rev Public Health*. 2022;43:59–78. https://doi.org/10.1146/annurev-publhealth-051920-110928.