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Healthcare Inequalities in Autism Services: Evidence from the United States, Africa, and High-Income Countries Using Machine Learning

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Abstract: This article presents a refined empirical framework for studying global disparities in autism spectrum disorder (ASD) diagnosis and service access across the United States, selected African countries, and high-income comparator countries. Unlike earlier drafts that treated the subject as a generic macroeconomic panel problem, the present manuscript is aligned with the accompanying data workbook, which identifies concrete sources for country-level ASD prevalence and burden estimates, U.S. Autism and Developmental Disabilities Monitoring (ADDM) Network surveillance measures, World Bank development indicators, WHO policy benchmarks, and optional clinical imaging data from ABIDE. The paper is written as a reproducible data-driven study rather than a claim of completed causal estimation: where the workbook provides templates rather than populated country-year values, the text distinguishes actual data sources from proposed estimands. The conceptual argument is that observed autism prevalence is not only a neurodevelopmental measure; it is also shaped by diagnostic infrastructure, clinical workforce capacity, school-based screening, insurance coverage, social awareness, stigma, income, and digital readiness. The proposed analytical design combines descriptive inequality indices, multilevel regression, Oaxaca–Blinder decomposition, random forest, gradient boosting, and SHAP-based explainability to identify the predictors most associated with cross-national differences in autism identification. The central contribution is a transparent, human-centered methodology for comparing autism diagnosis systems without overstating causal claims. The article emphasizes that lower reported prevalence in many African countries should not be interpreted as lower underlying need, because underdiagnosis, late identification, and limited surveillance capacity remain central measurement challenges. Policy implications focus on early screening, workforce development, culturally valid tools, telehealth, data infrastructure, and ethically governed AI systems for low-resource settings.

Keywords: *Autism Spectrum Disorder; Diagnosis Disparities; Africa; United States; Machine Learning; SHAP; Health Inequality; Early Identification; Global Mental Health.*

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I. INTRODUCTION

Autism spectrum disorder (ASD) is a lifelong neurodevelopmental condition characterized by differences in social communication, behavior, sensory processing, and adaptive functioning. Contemporary epidemiological evidence indicates that ASD is found in all regions of the world, yet the probability that a child will be identified, formally diagnosed, and connected to appropriate services varies sharply across health systems. In the United States, surveillance infrastructure has expanded through the CDC Autism and Developmental Disabilities Monitoring Network, which reported that about one in 31 children aged eight years was identified with ASD in 2022 across participating sites (Shaw et al., 2025). Globally, the World Health Organization and the Global Burden of Disease Study estimate that approximately one in 127 people were autistic in 2021, while also emphasizing that characteristics may appear in early childhood but diagnosis often occurs much later (World Health Organization, 2025; Global Burden of Disease 2021 Autism Spectrum Collaborators, 2025). These differences show why autism statistics must be interpreted as products of both underlying neurodevelopmental prevalence and the visibility of diagnostic systems.

The study of global autism disparities is particularly important when comparing the United States with African countries and other high-income countries. The United States and several high-income comparators have relatively established child health surveillance systems, pediatric referral pathways, school-based evaluation systems, and advocacy networks. Many African countries, by contrast,

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face constrained specialist workforces, limited public awareness, fragmented registries, and uneven access to developmental assessment. These differences do not imply that autism is rare in Africa. Rather, they suggest that measured prevalence and age at diagnosis may be heavily influenced by health-system capacity, social stigma, and availability of culturally valid screening tools. A scientifically defensible analysis must therefore avoid the simplistic interpretation that lower recorded prevalence equals lower true prevalence. Instead, the empirical focus should be on diagnosis visibility, service access, and the predictors of early identification.

The attached data workbook provides a useful foundation for such a study. It identifies core datasets and variables rather than a fully populated final analysis file. The workbook lists the CDC ADDM Network for U.S. surveillance, the IHME Global Burden of Disease Results Tool and Our World in Data for country-year ASD-related prevalence or burden measures, World Bank World Development Indicators for socioeconomic predictors, WHO for global epidemiological and policy context, UNDP for human development indicators, and ABIDE for optional machine-learning validation using individual-level neuroimaging data. It also provides a machine-learning variable schema with country, ISO code, year, region group, ASD prevalence rate, ASD cases, DALY rate, GDP per capita, health expenditure, physician density, urbanization, internet use, school enrollment, sex, race/ethnicity, site, and model target. The revised paper uses those elements as the basis for a coherent empirical design.

The purpose of this article is therefore threefold. First, it refines the theoretical and empirical framing of healthcare inequalities in autism services so that the paper speaks directly to autism diagnosis rather than to generic macroeconomic outcomes. Second, it translates the data workbook into a reproducible methodology suitable for a future full empirical paper. Third, it proposes a machine-learning and explainable-AI strategy that can identify which health-system and socioeconomic factors are most associated with differences in autism identification across the United States, Africa, and high-income comparators. The revised manuscript deliberately removes unsupported claims of completed fixed-effects, GMM, IV, and SHAP estimates that were not grounded in the attached dataset. In their place, it provides a transparent analytical framework, model equations, variable definitions, and interpretation plan that can be implemented once the source datasets are downloaded and merged.

This correction is important for academic integrity. A paper on autism disparities should not report country-year regression coefficients, mediation percentages, or machine-learning feature importances unless those estimates were produced from a real populated dataset. The data workbook is strongest as a reproducibility map: it tells the researcher where to obtain the variables and how to structure the merged panel. The revised article preserves the original paper's broad organization, length, and academic tone, but it changes the substance so that the claims match the evidence. It also adopts a human-centered perspective: the goal of AI in autism research is not to replace clinicians or reduce autistic people to risk scores, but to support earlier, fairer, and more culturally responsive pathways to identification and care.

II. LITERATURE REVIEW

The autism diagnosis literature has moved through several phases. Early epidemiological studies documented rising diagnosed prevalence in high-income countries, with debates over the relative roles of broader diagnostic criteria, improved awareness, service incentives, environmental hypotheses, and surveillance methods. Subsequent work showed that measured prevalence is highly sensitive to case-finding procedures, record access, age groups, and the definition of diagnosis or identification. In the United States, ADDM estimates are surveillance-based and site-specific; they should not be treated as a simple national census. At the same time, these estimates remain among the strongest public sources for examining diagnosis timing, demographic differences, and early identification. The newest ADDM report highlights both high overall prevalence and wide variation across sites, reinforcing the importance of local service systems in shaping observed identification (Shaw et al., 2025).

A major strand of research examines disparities within countries. In the United States, studies have identified differences by race, ethnicity, sex, socioeconomic status, language background, and geography. Historically, White children were often identified earlier than Black, Hispanic, or immigrant-background children, although recent ADDM reports suggest that the racial and ethnic pattern of identified prevalence has shifted in some sites. Sex differences remain substantial, partly because autism may be under-recognized in girls and women, particularly when traits are camouflaged or accompanied by internalizing symptoms. Diagnostic disparities also interact with insurance status, family income, school resources, and proximity to developmental specialists. These findings matter for global comparison because the same mechanisms—resources, awareness, clinician training, stigma, and institutional access—operate across countries, though with different intensity.

The African autism literature is smaller but rapidly expanding. Reviews consistently report limited epidemiological surveillance, late diagnosis, under-recognition, stigma, reliance on tertiary clinics, and a shortage of trained specialists. In many settings, families may first seek help from general practitioners, teachers, religious leaders, or traditional healers before reaching a specialist. Formal diagnosis can be delayed by cost, distance, limited speech and language services, and lack of validated instruments in local languages. Research from South Africa, Nigeria, Ghana, Kenya, Ethiopia, and other countries suggests that autism is present across the continent but frequently hidden by weak service infrastructure. This means that African data must be interpreted carefully: sparse

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administrative records may reflect service scarcity rather than low need.

High-income comparator countries provide an additional lens. The United Kingdom, Canada, Australia, Japan, South Korea, Germany, France, and Nordic countries differ in their health financing systems, special education policies, registry infrastructure, and cultural attitudes toward disability. Some countries rely more heavily on educational records, others on clinical registries, and others on insurance or administrative databases. These institutional differences are directly relevant to machine learning because a model trained on one country's observed diagnoses may learn local service rules rather than universal indicators of need. Cross-country prediction must therefore treat the country context as a potential source of measurement bias, not merely as a nuisance variable.

Global burden estimates from IHME and the Global Burden of Disease Study are useful for broad comparative work because they provide country-year estimates across long time periods, age groups, and sexes. However, they should not be confused with direct diagnosis registries. Burden estimates combine available data, modeling assumptions, covariates, and uncertainty intervals. They are appropriate for estimating broad patterns of prevalence, disability-adjusted life years, and years lived with disability, but they cannot by themselves answer questions about age at first diagnosis or access to therapy. The revised paper therefore treats GBD/IHME variables as global prevalence and burden proxies, while treating CDC ADDM and national registry data as more appropriate sources for diagnosis timing and early identification outcomes.

Machine learning has increasingly entered autism research through three main routes. The first is screening and behavioral prediction, where algorithms use questionnaire responses, developmental history, or caregiver-reported behaviors to predict likelihood of ASD. The second is clinical classification using neuroimaging, eye tracking, speech, genetics, or digital phenotyping. The third is health-services research, where machine learning identifies predictors of diagnosis delay, service use, or inequitable access. For the present topic, the third route is most relevant. The goal is not to diagnose individual children using an opaque model; it is to understand which system-level conditions predict whether autistic children are likely to be seen, assessed, and connected with support.

Explainable AI is especially important in autism disparities research because purely predictive models can reproduce structural inequities. For example, if a model uses prior specialist visits as a strong predictor of diagnosis, it may perform well statistically while reinforcing unequal access: children without specialists would appear low-risk not because they lack autism traits but because they lack contact with the system. SHAP, LIME, partial dependence plots, and counterfactual explanations can help identify such risks, but they do not solve them automatically. Researchers must decide whether a predictor represents true clinical need, diagnostic opportunity, or social advantage. The literature on algorithmic fairness, health equity, and responsible AI therefore belongs at the center of this study.

A final gap in the literature is the limited integration of global health data with AI-based disparity analysis. Many autism studies focus either on high-income clinical samples or on qualitative accounts of service challenges in low-resource settings. Fewer studies build a cross-national panel that links ASD prevalence or diagnosis indicators to GDP per capita, health expenditure, physician density, urbanization, internet use, education, and regional groupings. The accompanying workbook points directly toward this gap. It provides a schema for comparing the United States, African countries, and high-income comparators using harmonized predictors and transparent source documentation. This revised article positions the study as a bridge between autism epidemiology, global health equity, and explainable machine learning.

III. DATA SOURCES AND VARIABLE CONSTRUCTION

The revised study is based on a multi-source data architecture. The global country-year component should be built from IHME/GBD and Our World in Data autism-related indicators, merged with World Bank and UNDP covariates. The U.S. surveillance component should be built from CDC ADDM site-year data, including prevalence among children aged four and eight years, age at evaluation, age at diagnosis where available, race/ethnicity, sex, and site-level measures. The optional clinical AI component can use ABIDE I/II for individual-level neuroimaging classification, but that component should be clearly separated from the health-services disparity analysis because ABIDE is not designed to estimate national diagnosis inequities.

The country-panel template in the workbook contains the most important structure for the main analysis. Each row represents a country-year observation. The proposed variables include country, ISO3 code, region group, income group, year, ASD prevalence rate, ASD cases, ASD DALY rate, GDP per capita, health expenditure per capita, physicians per 1,000 people, urban population percentage, internet users percentage, source of ASD data, source of covariates, and notes. The region group variable should distinguish the United States, Africa, high-income comparators, and other countries. For the current paper, the key comparison is the United States versus African countries versus high-income comparators. The model should not treat Africa as a single homogeneous unit; where sample size permits, regional and income-group interactions should be examined.

The dependent variable depends on the research question. If the analysis focuses on global diagnosis visibility, the target can be ASD prevalence rate or the log of ASD prevalence rate from GBD/IHME. If the analysis focuses on burden, the target can be ASD DALY rate or years lived with disability. If the analysis focuses on early diagnosis, the target

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should be age at first diagnosis, evaluation by 36 months, or identification by 48 months; these measures are more likely to come from CDC ADDM or national registries than from global burden data. Because many African countries lack comparable diagnosis-age data, the study should be explicit about missingness and avoid overgeneralizing from incomplete sources.

The main predictors reflect diagnostic capacity and social opportunity. GDP per capita captures general development and family resource context. Health expenditure per capita captures health-system investment. Physicians per 1,000 people approximates clinical workforce availability, although it does not directly measure developmental pediatricians, child psychiatrists, psychologists, speech therapists, or occupational therapists. Urbanization may proxy geographic access to specialists and schools. Internet use can proxy digital readiness for telehealth, online parent education, and AI-assisted screening. School enrollment can proxy contact with institutions that may observe developmental differences. Income group and region group capture structural context that may shape both service access and data quality.

The CDC ADDM template in the workbook provides a separate U.S. structure. It includes surveillance year, site, age group, sex, race/ethnicity, ASD prevalence per 1,000, identified by 48 months, evaluation by 36 months, median age at first evaluation, median age at diagnosis, source URL, and notes. This dataset is valuable for the U.S. portion of the study because it moves beyond prevalence toward identification timing. However, ADDM site data should not be interpreted as nationally representative in a simple way. It is best used to examine variation across surveillance sites and demographic groups within the United States, then to compare the U.S. surveillance infrastructure with the more limited data availability in many African countries.

The revised paper treats missingness as substantively meaningful. In autism service research, missing data are not merely a technical inconvenience. Missing country-year values may indicate weak registry systems, absence of surveillance, limited specialist services, or lack of public reporting. Therefore, the analysis should include both a complete-case model and a missingness model. A binary variable indicating whether a country has usable ASD prevalence or diagnosis data can be modeled as an outcome. This approach helps distinguish true service differences from data-system differences. It also prevents the paper from presenting a clean numerical comparison that hides the very inequalities it seeks to study.

All variables should be documented with source URLs and version dates. The workbook already lists direct access links for OWID/IHME, IHME GBD, CDC ADDM, WHO, World Bank WDI, UNDP HDI, and ABIDE. In the final empirical article, every row of the merged dataset should preserve source metadata, including the source of the autism measure and the source of the covariates. This is important because autism estimates from GBD, CDC, registries, and clinical datasets have different meanings. A high-quality paper should make those differences visible rather than mixing them as if they were identical measurements.

Table 1 Primary Data Sources from the Attached Data Workbook

Dataset	Geography	Main variables	Use in study
CDC ADDM Network	United States sites	ASD prevalence among children aged 4 and 8; early identification measures	U.S. benchmark for diagnosis and identification timing
IHME / GBD Results Tool	Global	ASD prevalence, cases, DALYs, YLDs, rates, counts	Country-year prevalence and burden proxy
Our World in Data / IHME	Global	Autism and neurodevelopmental disorder indicators	Open CSV source for global comparison
World Bank WDI	Global	GDP, health expenditure, physicians, urbanization, internet use	Socioeconomic and health-system predictors
WHO Autism Fact Sheet	Global	Global prevalence benchmark and policy context	Background and public health framing
ABIDE I/II	Multi-site clinical sample	ASD/control status, age, sex, imaging features	Optional AI validation; not national disparity data

Note. The workbook provides source links and templates. It does not by itself contain a fully populated final country-year analysis panel.

Table 2 Core Variables for the Proposed Machine-Learning Dataset

Variable	Level	Source	Role	Interpretation
asd_prevalence_rate	Country-year	IHME/GBD or OWID	Target	Reported or modeled prevalence; visibility-sensitive
identified_by_48_months	Site-year / child group	CDC ADDM or registry	Target	Early identification indicator
gdp_per_capita	Country-year	World Bank WDI	Feature	General resource context
health_exp_pc	Country-year	World Bank WDI	Feature	Health-system investment
physicians_per_1000	Country-year	World Bank WDI	Feature	Provider capacity proxy

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urban_pop_pct	Country-year	World Bank WDI	Feature	Geographic service access proxy
internet_users_pct	Country-year	World Bank WDI	Feature	Digital readiness for awareness and telehealth
region_group	Country-year	Researcher-coded	Feature stratifier	USA, Africa, high-income comparator, other

Note. Variables follow the schema supplied in the attached workbook and should be harmonized before modeling.

IV. METHODOLOGY

The empirical strategy has four connected components: descriptive inequality analysis, multilevel regression, machine-learning prediction, and explainable-AI interpretation. The descriptive component compares reported ASD prevalence, diagnosis-related indicators, and data availability across the United States, African countries, and high-income comparators. The multilevel regression component estimates associations between country-year predictors and ASD-related outcomes while accounting for repeated observations over time. The machine-learning component evaluates whether nonlinear models improve prediction relative to conventional regression. The explainability component examines whether the model's predictions are driven by meaningful clinical and system factors or by proxies for data privilege.

For the country-year panel, the baseline statistical model can be specified as: $\ln(ASDRate_{it}) = \alpha + \beta1Africa_i + \beta2HighIncome_i + \beta3\ln(GDPpc_{it}) + \beta4\ln(HealthExp_{it}) + \beta5Physicians_{it} + \beta6Urban_{it} + \beta7Internet_{it} + \mu_i + \tau_t + \varepsilon_{it}$. Here, $ASDRate_{it}$ is the ASD prevalence or burden rate for country i in year t; $Africa_i$ and $HighIncome_i$ are group indicators; μ_i represents country-specific unobserved heterogeneity; τ_t captures global year shocks; and ε_{it} is the error term. If country fixed effects are included, time-invariant group indicators are absorbed, so group comparisons should be estimated either in pooled models with robust controls, random-intercept multilevel models, or interaction models with time-varying predictors.

A multilevel model is particularly appropriate because countries are nested within regions and income groups. One specification is: $y_{it} = \alpha + X_{it}\beta + u_{region} + u_{country} + \tau_t + \varepsilon_{it}$, where u_{region} and $u_{country}$ are random intercepts. This model allows the study to estimate how much variation lies between regions, between countries within regions, and within countries over time. For the U.S. ADDM component, a similar hierarchical model can be estimated with children or site-year observations nested within surveillance sites and years. Race/ethnicity, sex, site, and age group can be included as predictors of prevalence, early evaluation, or identification by 48 months.

The Oaxaca–Blinder decomposition can be used to separate explained and unexplained differences between group means. For example, the difference in reported ASD identification between high-income comparators and African countries can be decomposed into a component explained by GDP per capita, health expenditure, physician density, urbanization, and internet access, and an unexplained component that may reflect unmeasured factors such as stigma, registry quality, educational policy, or measurement error. The decomposition should be interpreted carefully because unexplained differences are not automatically discrimination; they are residual differences after observed covariates are included.

The machine-learning component should compare logistic regression, random forest, XGBoost or LightGBM, and CatBoost depending on the final target. If the outcome is continuous, such as ASD prevalence rate, the study can use regression models and evaluate root mean squared error, mean absolute error, and out-of-sample R-squared. If the outcome is binary, such as whether a country-year is above the global median identification rate or whether a child/site was identified by 48 months, the study can use classification models and evaluate AUC, precision, recall, F1 score, calibration, and subgroup performance. Cross-validation should be grouped by country where possible to reduce leakage from repeated country-year observations.

Explainability should be conducted with SHAP values, permutation importance, partial dependence plots, and subgroup error analysis. SHAP can identify whether the model relies most heavily on health expenditure, physician density, GDP, urbanization, internet access, or region group. However, SHAP values must be interpreted in light of the measurement problem. If the model finds that internet access is a strong predictor, the substantive interpretation may be that digital infrastructure improves awareness and service access, but it may also mean that countries with better digital infrastructure have better reporting systems. The paper should therefore distinguish predictors of autism occurrence from predictors of autism recognition.

Ethical safeguards are essential. AI models used in autism research can unintentionally pathologize neurodiversity, reinforce deficit-based assumptions, or under-serve groups missing from training data. The methodology should therefore include fairness assessment by sex, region, income group, and where available race/ethnicity. Calibration should be checked separately for the United States, Africa, and high-income comparators. If model performance is poor for African countries because of sparse data, the paper should report this limitation clearly rather than presenting the model as globally valid. Responsible AI in this context means improving visibility, access, and support, not automating exclusion.

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Table 3 Recommended Empirical Models And Interpretation

Model	Outcome	Purpose	Key caution
Descriptive inequality indices	Data availability, prevalence, early identification	Map visible disparities	Do not treat missing countries as irrelevant
Multilevel regression	Reported ASD rate or diagnosis timing	Estimate associations with system predictors	Association is not causation
Oaxaca–Blinder decomposition	Group differences	Separate explained from residual disparities	Residual is not automatically discrimination
Random forest / boosting	Continuous or binary target	Capture nonlinear patterns	Check subgroup performance
SHAP explainability	Model predictions	Interpret model drivers	Predictors may reflect visibility, not autism occurrence
Fairness and calibration tests	Prediction errors	Assess equity across groups	Poor performance for Africa must be reported

Note. The preferred design combines transparent statistical modeling with machine-learning models and explain ability checks.

V. ANALYTICAL FRAMEWORK AND EXPECTED OUTPUTS

Because the attached workbook is a structured data package rather than a completed empirical dataset, the results section must be reframed as an analytical roadmap. The appropriate output is not a table of invented coefficients, but a set of reproducible tables and figures that can be produced after the listed sources are downloaded and merged. The first output should be a source-coverage table showing which countries have ASD prevalence data, which have diagnosis-timing data, and which have service-access covariates. This table is central to the paper because data availability itself is part of the inequality under study.

The second output should be a descriptive comparison of the United States, Africa, and high-income comparators. For each group, the paper should report the number of countries, years covered, mean reported ASD prevalence rate, median prevalence rate, interquartile range, share of missing values, mean GDP per capita, mean health expenditure per capita, physician density, urbanization, and internet access. These descriptive statistics will allow readers to see whether reported prevalence tracks health-system capacity. The table should include uncertainty intervals where available, especially for GBD estimates.

The third output should be a figure showing reported ASD prevalence or burden over time by group. The figure should not imply that differences are purely biological. It should be captioned as reported or modeled prevalence, emphasizing that observed rates reflect both underlying autism and identification systems. If African countries show lower reported prevalence than high-income comparators, the discussion should interpret that pattern through surveillance and access constraints rather than as evidence of lower need.

The fourth output should be a regression table that begins with a simple pooled model and then adds socioeconomic predictors, health-system predictors, region fixed effects, and year fixed effects. A more advanced model can use multilevel random effects. The key question is whether health expenditure, physician density, urbanization, and internet access predict higher reported ASD identification after controlling for income. A positive coefficient should be interpreted as evidence of greater visibility or diagnostic capacity unless the outcome is a direct burden estimate with carefully modeled uncertainty.

The fifth output should be a machine-learning model comparison table. Logistic regression or linear regression should serve as transparent baselines. Random forest and gradient boosting can then test whether nonlinear interactions improve prediction. The model comparison should include cross-validated performance and subgroup performance. A model that performs well overall but poorly for African countries would not be acceptable for policy use without substantial caution. The paper should also report whether removing region or income-group variables changes performance, because these variables may capture structural inequality rather than causal mechanisms.

The sixth output should be a SHAP summary plot and a SHAP dependence plot for the top predictors. For example, if health expenditure per capita and physician density are among the strongest predictors, that would support the argument that diagnostic capacity influences observed autism identification. If region group dominates the model, the interpretation should be that unmeasured institutional and cultural differences remain substantial. SHAP analysis should be used to make the model transparent, but not to claim causation.

The seventh output should be a missingness analysis. Countries with no usable ASD data should not disappear from the study. Instead, the paper should model the probability of data availability as a function of GDP, health expenditure, income group, region, and internet access. This analysis is crucial because the absence of autism data can itself be a signal of weak surveillance systems. A global autism disparities paper that excludes countries with poor data may reproduce the invisibility it aims to challenge.

The expected contribution of the completed analysis is therefore not a single causal estimate. It is a layered account of how autism identification is associated with national

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resources, health-system capacity, data infrastructure, and social context. The results should answer three questions: Who is visible in autism data? Which systems make diagnosis more likely or earlier? Where is AI most likely to help, and where might it amplify existing disparities?

Table 4 Planned Outputs after the Data Package is Fully Populated

Output	Description	Why it matters
Source coverage table	Countries, years, and variables available by source	Shows data inequality directly
Group descriptive statistics	USA, Africa, high-income comparators	Provides interpretable baseline comparison
Time trend figure	Reported ASD prevalence or burden over time	Distinguishes visibility from underlying need
Regression table	Associations between system predictors and ASD visibility	Tests health-system explanations
ML comparison table	Cross-validated model performance and subgroup performance	Shows whether AI improves prediction equitably
SHAP summary plot	Top predictors of model output	Explains model drivers and potential bias
Missingness model	Predictors of whether data exist	Treats invisibility as a substantive outcome

Note. These are planned outputs; numerical estimates should be reported only after real source files are downloaded and merged.

VI. DISCUSSION

The refined article changes the interpretation of autism service inequality in an important way. Instead of treating autism outcomes as comparable across all countries without qualification, it recognizes that diagnosis is a pathway shaped by institutions. A child with similar developmental characteristics may be identified early in one country, identified late in another, and never formally diagnosed in a third. The difference is not only clinical; it is social, economic, educational, and political. This is why the proposed study compares health expenditure, physician density, urbanization, internet access, and school-related indicators across regions. These variables help explain who enters the diagnostic system and who remains invisible.

For the United States, the key issue is not the absence of surveillance but unequal access and variable timing. ADDM data show high identified prevalence and continuing site variation. Within the U.S., disparities can occur across race/ethnicity, sex, language, insurance, state policy, rurality, and school district resources. A strong U.S. analysis should therefore focus on early evaluation, early identification, service connection, and demographic differences rather than prevalence alone. High prevalence does not automatically mean equitable care. It may reflect improved identification in some groups while other groups still face delays or insufficient services.

For African countries, the central issue is often visibility. Many countries lack routine ASD surveillance, and available studies may come from tertiary clinics or urban centers. This creates selection bias: children who reach specialist clinics are not representative of all autistic children. Families in rural areas, low-income households, and communities with high stigma may remain outside the data. Therefore, the research question should be framed around diagnostic and service disparities rather than around simplistic prevalence comparison. Machine learning can help identify structural predictors of low visibility, but it cannot substitute for investment in community-based surveillance and culturally valid assessment.

For high-income comparators, the study can identify alternative policy models. Countries with universal health coverage, national disability registries, integrated early-childhood screening, or strong school-based support may provide lessons for improving access. However, high-income countries also differ widely in waiting times, adult diagnosis pathways, cultural recognition, and service eligibility rules. A comparative study should therefore examine not only whether autism is identified, but how identification translates into supports. Diagnosis without services is an incomplete policy success.

AI has potential value in this field when used carefully. It may help prioritize referrals, screen developmental risk in settings with few specialists, translate parent-reported information into structured risk indicators, and identify service gaps from administrative data. In low-resource settings, AI-enabled telehealth and mobile screening tools could expand reach if they are culturally adapted, language-sensitive, and evaluated locally. Yet AI can also cause harm if models trained on U.S. or European populations are exported to African contexts without validation. Cultural differences in communication, caregiver reporting, school access, and clinical expectations may reduce model validity.

The most defensible role for explainable AI in this paper is therefore diagnostic-system analysis, not automated diagnosis. Models can ask which national and service variables explain observed differences in identification. SHAP values can reveal whether model predictions are driven by income, health expenditure, workforce, urbanization, or digital access. Fairness analysis can show whether prediction errors are concentrated in Africa or among lower-income settings. This framing is both scientifically safer and more aligned with global health equity.

The policy implications are practical. First, countries need early developmental screening integrated into primary care and schools. Second, African health systems need workforce development in developmental pediatrics, psychology, speech-language therapy, occupational therapy, and special education. Third, screening tools must be

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translated, culturally adapted, and validated rather than simply imported. Fourth, governments should build autism registries and data systems that protect privacy while enabling planning. Fifth, AI tools should be evaluated for fairness, calibration, and local usability before deployment. Finally, families and autistic people should be involved in research design so that the outcome is not merely more diagnosis, but better support, dignity, and inclusion.

Table 5 Policy Implications by Comparison Group

Group	Main challenge	Policy response
United States	High identification but uneven timing and services	Improve early evaluation, insurance coverage, rural access, and culturally responsive care
African countries	Low visibility, limited surveillance, specialist shortages	Build workforce, registries, primary-care screening, school pathways, and local validation
High-income comparators	Variation in registries, wait times, and service eligibility	Compare policy models and track diagnosis-to-service pathways
Global AI systems	Risk of exporting biased models	Require local validation, fairness testing, transparency, and community participation

Note. The policy goal is not merely more diagnosis, but timely support and inclusion.

VII. CONCLUSION

This revised manuscript provides a more accurate and human-centered foundation for studying global disparities in autism diagnosis and services. It aligns the paper with the attached data workbook by using the workbook's real source structure: CDC ADDM for U.S. surveillance, WHO for global context, IHME/GBD and Our World in Data for country-level burden and prevalence proxies, World Bank and UNDP for socioeconomic covariates, and ABIDE as an optional clinical AI dataset. The revision removes unsupported claims of completed econometric and machine-learning estimates and replaces them with a transparent methodology that can be implemented after the source data are downloaded and merged.

The central argument is that autism diagnosis disparities are not simply differences in neurodevelopmental prevalence. They are differences in visibility, surveillance, resources, specialist access, school systems, stigma, and policy. Comparing the United States, Africa, and high-income countries requires careful attention to measurement. Lower reported prevalence in low-resource settings should be interpreted cautiously because it may reflect underdiagnosis and weak data systems. Conversely, higher identified prevalence in the United States may reflect stronger surveillance and service pathways, but it does not eliminate disparities in timing or support.

The proposed methodology combines descriptive inequality analysis, multilevel modeling, Oaxaca–Blinder decomposition, machine-learning prediction, and SHAP-based explainability. This combination is appropriate because autism disparities are nonlinear, multilevel, and shaped by interactions between health systems and socioeconomic conditions. The methodological contribution lies in using AI to make diagnostic systems more transparent while avoiding the ethical mistake of treating algorithmic predictions as neutral truth.

Future research should complete the empirical pipeline using fully downloaded and cleaned data. The next step is to populate the country-panel template, add U.S. ADDM supplementary data, code country groups, harmonize variable definitions, and run the planned models with subgroup validation. A publishable version should report actual results only after this process is complete. The strongest contribution will come from combining rigorous quantitative analysis with humility about data limitations and respect for autistic people and families across diverse cultural contexts.

LIMITATIONS

The main limitation is that the attached workbook is a data package and template rather than a completed empirical dataset. It identifies credible sources and variables, but many numerical values still need to be downloaded and merged. Consequently, this refined article should be read as a reproducible study design and literature-grounded manuscript, not as a final results paper. A second limitation is measurement comparability. CDC ADDM surveillance, GBD modeled estimates, national registries, clinical samples, and school records measure different constructs. Combining them requires careful labeling and sensitivity analysis.

A third limitation concerns diagnosis timing outside high-income settings. Many African countries do not have nationally representative autism diagnosis-age data. If the final analysis relies only on countries with available data, it may overrepresent better-resourced systems. The missingness analysis proposed above is therefore essential. A fourth limitation is that AI models may perform poorly in countries underrepresented in the training data. This is not simply a technical problem; it is an equity problem. The paper should report such weaknesses openly and use them to motivate investment in data systems rather than to rank countries unfairly.

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