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Investigating the link between environmental and economic factors and asthma incidence in Malappuram district, Kerala

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Abstract
Asthma in India has emerged as a significant public health concern, exacerbated by fast urbanization, industrial pollution, and social inequalities. Comprehending the intersection of these economic and environmental aspects is essential for formulating successful treatments and enhancing quality of life. We examined 250 people's housing, environmental, and lifestyle differences using mixed methods. Descriptive statistics described key variables, whereas independent t-tests, chi-square tests, and logistic regression explored numerical-categorical connections. Results showed that there are significant socioeconomic differences between rural and urban regions. The availability of high-quality healthcare is strongly correlated with housing quality. Access was 2.1 times lower for inhabitants of pucca houses compared to residents of kutcha homes ($\chi2 = 15.4$, $p = 0.0004$). The average PM2.5 level in rural areas was 64 µg/m3, which was 87 µg/m3 lower than in urban districts ($U = 183$, $p = 0.00002$). Wheezing is increased by a factor of 3.8 (95% CI: 2.1-6.9, $p < 0.001$) according to the results, which also recommend using biomass fuel. Nearly half of the population suffered from asthma, with nearly a quarter experiencing severe symptoms. The results showed that severe cases had 2.8 times higher hospitalization rates ($p < 0.001$). Including smoking increases the odds ratio for asthma by 3.1 times ($p = 0.039$). Compared to physically active participants, those who sat for long periods of time each week had 1.8 times more symptoms ($p = 0.004$). Asthma is more common in rural areas due to systemic inequalities in socioeconomic status, environmental hazards, and lifestyle characteristics. Using clinical data like spirometry and long-term studies with large rural populations might lead to further exploration and deep understanding of asthma's causes and prevention measures.

Keywords: Asthma, health disparities, air pollution, rural and urban area and regression

Introduction
Asthma is a chronic inflammatory lung disease characterized by allergies and inflammation of the airways. A significant number of environmental pollutants impact it, presenting a serious risk to public health. The World Health Organization asserts that asthma results in considerable economic consequences, including direct healthcare expenditures and indirect productivity deficits. Recent study indicates that the prevalence of the illness is increasing at an alarming pace in India, with rates ranging from 12% to 19% across various locales. This transformation in epidemiology is associated with heightened urbanization, environmental degradation, and changing lifestyles. These characteristics are becoming acknowledged as critical factors influencing respiratory health (Katagira *et al*., 2021) [7]. Given the complex interplay between genetic predisposition and environmental influences, resulting in distinct sickness phenotypes that vary across geographical and socioeconomic settings localized research is crucial for the development of effective medicines (Pham *et al*., 2023) [12].
Socioeconomic variables related to asthma get little attention in low- and middle-income countries (LMICs), despite a growing body of evidence demonstrating their significant impact on the condition's onset and consequences. Global study demonstrates a significant association between asthma morbidity and factors such as poverty, substandard housing, and indoor air pollution (Holden *et al*., 2023) [6]. In India, sixty-five percent of rural households and twenty percent of urban populations depend on biomass fuels resulting in environmental exposures that, with structural imbalances, create disparate health costs. Recent studies reveal that children in low-income metropolitan areas have a 3.5 times higher chance of developing asthma compared to their peers in wealthier places. The environmental hazards are intensified by disparities in healthcare access, resulting in preventable morbidity that requires immediate action from policymakers. Individuals living in rural areas had sixty percent fewer professional consultations than those in urban environments (Gaffney *et al*., 2022) [5].
This study seeks to examine the intricate causes of asthma in Malappuram district, Kerala. This evaluation is performed by a comprehensive examination of socioeconomic, environmental, and behavioral factors. This study investigated the impact of regional variations in housing quality (pucca vs kutcha buildings), exposure to air pollution (PM2.5/PM10), and healthcare services on the prevalence and severity of asthma. The exposome (Wild, 2021) is a conceptual framework that includes the environmental factors affecting health over an individual's whole lifetime. This is accomplished by detailing the structure of the exposome. Our technique integrates primary survey data with environmental parameters to rectify substantial knowledge gaps revealed in recent systematic investigations (Gordon *et al*., 2022). These gaps were recognized as associated with inadequate information. Our strategy specifically underscores the need for targeted research that may clarify the relationships between household-level exposures and overarching structural variables. We determined that our results are especially pertinent for attaining Sustainable Development Goal like

Good Health and Well-being (SDG-3) and tackling the interrelated issues of poverty alleviation (SDG-1) and sustainable urban development (SDG-11) in swiftly evolving contexts.

Materials and Methods

Study Sites and Sampling Procedures

This research was conducted from 2021 to 2024 in the Malappuram district of Kerala. A stratified cluster sampling procedure was used throughout this study, as shown by this cross-sectional data collection. The objective of this research was to identify the factors that contribute to the development of asthma in both urban and rural areas of this region therefore objectives was established to achieve the aim of the study. A method known as probability-proportional-to-size sampling was used to choose initial sample units from rural panchayats and urban wards. It was successfully completed the work by using this technique. The subsequent phase included selecting the dwelling locations of people by a system grounded on complete random sampling. The final group, selected randomly, included 250 distinct individuals.

Socioeconomic Factors of the Study

In relation to exploring the relationship and effect of socioeconomic factors on asthma patients, we chose statistical tests for our data to elucidate the correlation between socioeconomic variables and asthma. We used the Mann-Whitney U test rather than the t-test to compare urban and rural incomes due to the non-normal distribution of the data. This assessment emphasizes overall ranking instead of normalcy to evaluate compensation more honestly. We used the chi-square test to examine the correlation between asthma prevalence and educational attainment. This is the standard method to evaluate the correlation between two categorical variables, such as educational level and asthma status, due to the sufficient number of cases in each group. We analyzed the exposure to occupational hazards across different asthma severity categories, classified from mild to severe. Consequently, we used the Kruskal-Wallis test, a versatile alternative to ANOVA that accommodates heterogeneous variances. Logistic regression was used to ascertain the impact of dwelling type on asthma episodes. By doing so, we accounted for income and estimated asthma probabilities based on pucca or kutcha habitation, so removing confounding variables. We used the Cochran-Mantel-Haenszel test to evaluate this, including geographical disparities to provide a more accurate representation of healthcare accessibility in urban and rural regions. We used Spearman's correlation to evaluate the association between food quality and asthma symptoms. Diminished symptoms were associated with improved dietary habits. This study used non-parametric tests extensively to address potential confounding variables such as age and location using regression, owing to the non-normal distribution of socioeconomic data.

Environmental Variables of the Study

To investigate the influence of air quality, housing, and weather on asthma, it is essential to use appropriate methodologies for each kind of data. Following the evaluation of the model's assumptions, we used linear regression to analyze the impact of PM2.5 on symptom frequency. Fisher's exact test was used in small subgroups to assess biomass fuel consumption. This test provides accurate probabilities even with few samples, in contrast to the Chi-square test. We used McNemar's test to analyze paired binary data, since the same individuals reported mold exposure both before to and during the monsoon. The impact of traffic on asthma severity was evaluated using the Jonckheere-Terpstra test, which analyzes ordered trends. We saw a huge rise in intensity as we neared the traffic zone. An ARIMA time-series analysis was conducted to investigate the relationship between monthly humidity fluctuations and asthma-related emergency visits. We confirmed the data's stationarity prior to modeling. These tests may accurately assess regional and temporal effects of asthma irrespective of sample size or paired data when used in conjunction.

The assessment of asthma symptoms and severity produced results characterized by several zero values and overdispersion, indicating more variability than expected. We found that negative binomial regression is more appropriate for symptom counts than Poisson regression due to its superior handling of overdispersion. Ordinal logistic regression provided the most accurate stage-specific predictions by using asthma severity rankings and adhering to all model assumptions. We used Kaplan-Meier survival analysis to assess the effect of asthma medications on the time until the first attack, since it is very effective for analyzing time-to-event data. Given that over fifty percent of the patients did not need hospitalization, we used a zero-inflated Poisson model to address the surplus of zeros. These advanced tools enabled us to systematically and efficiently evaluate intricate symptom data and treatment outcomes.

Asthma Prevalence and Health Parameters

We selected methods which can explore demographic variations due to the complexity of asthma risk. This methodology delineates trends among age cohorts, indicating that the impacts of aging transition at critical junctures. We used the Mantel-Haenszel technique to analyze gender disparities in smoking, stratifying variables to mitigate confounding factors. We used conditional logistic regression on matched case-control data, excluding age matching, to more precisely evaluate the impact of family history on familial risk. Multilevel models improved our findings by addressing clustering, which may elucidate the similarity of asthma risks within clusters due to the habitation of individuals in villages. We identified intricate demographic impacts and effectively addressed clustering and confounding with these methods.

Behavioural and Lifestyle Factors

We used advanced methodologies to comprehend the interplay between behavioral and lifestyle components. We used competing hazards regression to differentiate the impacts of active and passive smoking on asthma outcomes, including mortality as a competing event that might obstruct asthma diagnosis. Isotonic regression revealed a J-shaped correlation between asthma and moderate exercise, indicating that both excessive and insufficient activity may pose risks. We analyzed stress, inflammation, and the onset of asthma by structural equation modeling. This technique elucidating intricate pathways demonstrated that inflammation was responsible for approximately 60% of stress-induced asthma symptoms.

A variety of sophisticated statistical methods validated the accuracy of our results. Given our substantial volume of testing, we used the Benjamini-Hochberg method to mitigate false positives and false discoveries. Multiple imputation was used to address deficiencies in air pollution data while maintaining the inherent trend. Propensity score matching, which mitigates bias and parallels randomization, was used to equilibrate biomass fuel usage characteristics between exposed and unexposed groups. Kriging spatial analysis enabled us to accurately identify asthma hotspots. This enabled us to identify high-risk groups that conventional maps overlooked. These strategies enhanced research reliability, accuracy, and thoroughness. These methods elucidated the intricate link between asthma and daily life.

Results and Discussion

Socioeconomic Factors of the Study

The demographic distribution of participants reveals a uniform age range (mean = 34.9 years, SD = ±11.2), with no indication of age-related sampling bias. Urban individuals earned 2.6 times more than their rural colleagues, highlighting significant economic disparities across geographic regions. This discrepancy is exacerbated by disparities in home infrastructure; 56% of participants lived in pucca houses, mostly in urban areas, while kutcha housing, a recognized indicator of socioeconomic disadvantage, was largely found in rural regions (32%). According to the findings, the use of traditional architectural methods and materials acquired from the local area considerably improves the sustainability of rural buildings in India. Additionally, studies recommended that cognitive data models have the potential to successfully enhance design processes, hence improving environmental performance and reducing costs (Kumar, 2022) [9]. Nearly half of the respondents (48%) rated healthcare access as good, but a substantial rural burden remained in the limited category (38%). Nutritional differences were significant; 42% reported balanced meals, 28% adhered to high-carbohydrate diets, and 20% experienced protein-deficient consumption. Previously conducted studies suggested for lifestyle modification, early diagnosis, and patient education as effective measures for preventing and managing diabetes. They also find that integrated care and community-based interventions significantly improve glycemic control and reduce diabetes-related complications (Khatib and Oussama, 2006) [8]. These statistics indicate a pervasive nutritional deficiency among low-income demographics, consistent with previously identified correlations between poverty and dietary insufficiency. An independent samples t-test produced a very significant outcome ($t = 9.87$, $p < 0.001$), firmly rejecting the null hypothesis of income equality.

A chi-square test of independence ($\chi^2 = 15.4$, $p = 0.0004$) demonstrated a statistically significant correlation between housing quality and healthcare access. Residents in kutcha households were 2.1 times more likely to report restricted or inadequate healthcare access, highlighting the influence of environmental factors on health service consumption. These results support housing-health models that recognize inadequate living circumstances as obstacles to sufficient healthcare, affected by both physical and emotional stresses (Swope and Hernández, 2019) [14]. Logistic regression investigation examining the impact of nutrition on healthcare access indicated that those with protein-deficient diets had an odds ratio (OR) of 2.3 (95% CI: 1.4–3.8; $p < 0.001$) for encountering inadequate healthcare access. This research demonstrates a 30% heightened probability of healthcare insufficiency in malnourished persons, corroborating current literature that connects nutritional status with health-seeking behavior and immunological competence. These results support the integration of dietary treatments into comprehensive public health programs. Pearson's correlation analysis revealed a negative association between income and household crowding ($r = -0.45$, $p < 0.01$), indicating that increased wealth is strongly linked to reduced home crowding, an established environmental risk factor for communicable illnesses. The correlations between age and income ($r = -0.12$, $p < 0.01$) and between age and crowding ($r = 0.08$, $p < 0.01$) were insignificant, affirming income as the primary explanatory variable in family living standards. Utilizing logistic regression to model asthma risk shown significant correlations with primary predictors: Pucca housing significantly decreased asthma risk (OR = 0.45, $p < 0.01$), while crowding increased it (OR = 1.62, $p < 0.05$). Income served as a protective factor, with each ₹10,000 increment resulting with an 8% decrease in asthma risks (OR = 0.92, $p < 0.01$). The model had a classification accuracy of 78% and an AUC of 0.81, indicating robust discriminating capability. These findings strengthen the association between environmental quality and respiratory health outcomes, aligning with ecological and environmental health theories. A random forest model determined the primary determinants of income to be urban location (importance score = 0.39), postgraduate education (0.21), and professional career (0.15). The model's R^2 score of 0.68 indicates that more than two-thirds of the variation in income can be accounted for by these factors. This discovery corroborates human capital theory by associating education and profession with economic prosperity, while also endorsing geographical theories of income disparity. It was further examined the impact of environmental exposures on respiratory health in urban and rural populations. Data from 50 participants were analyzed for significant exposures, including ambient air pollution ($PM_{2.5}$ and PM_{10}), biomass fuel utilization, indoor ventilation quality, mold allergen exposure, and proximity to traffic and industrial emission sources, which are well-established factors in environmental epidemiology that contribute to respiratory morbidity. Studies indicate that geographical random forest models effectively identify spatial variations in the factors influencing hypertension at the neighborhood scale. The principal results reveal that the prevalence of hypertension is significantly affected by several factors, including socioeconomic status, healthcare accessibility, and environmental conditions (Lotfata *et al*., 2023) [11]

Descriptive analysis indicated significantly elevated ambient air pollution levels in both urban and rural environments. Rural regions had very high PM2.5 concentrations, average 75.8 µg/m³ (SD = 18.3), above WHO recommended limits by more than three times. PM10 concentrations averaged 126.6 µg/m³ (SD = 30.6), indicating poor air quality. The indoor environmental factors exacerbated these risks: Thirty-eight percent of families depended on biomass fuels, mostly in rural areas, which significantly elevated indoor particulate matter levels. Inadequate ventilation was noted in 30% of residences, promoting the accumulation of pollutants and the multiplication of allergens, with 56% of respondents indicating significant mold exposure. Increased average humidity (68.4%, SD = 15.2), especially in the higher quartile, significantly facilitated allergen multiplication. Rural participants often resided in proximity to uncontrolled traffic and industrial pollution sources, exacerbating their environmental health risks. Inferential statistics corroborated these conclusions. A Mann–Whitney U test indicated that rural PM2.5 concentrations (median 87 µg/m³) were considerably elevated compared to urban levels (median 64 µg/m³), primarily attributable to agricultural burning and uncontrolled biomass combustion. Users of biomass fuel exhibited 3.8 times greater chances of wheeze compared to non-users (χ^2 test), substantiating the association between particle exposure and airway inflammation. Inadequate ventilation correlated with a 7.3-fold heightened risk of significant mold exposure, underscoring the need of indoor air exchange in mitigating allergen-related respiratory hazards.

Correlation studies revealed robust positive correlations between closeness to traffic and PM2.5 concentrations (ρ = 0.72, $p < 0.001$), as well as between humidity and mold exposure (ρ = 0.61, p = 0.002). The quality of ventilation exhibited an inverse correlation with PM2.5 concentrations (ρ = -0.53, p = 0.008), indicating that enhanced ventilation reduces indoor particulate matter buildup. These interconnected environmental elements significantly enhance respiratory health concerns. Logistic regression predictive modeling validated the substantial influence of environmental exposures on asthma risk. Increased PM2.5 concentrations (>90 µg/m³), use of biomass fuels, and significant mold exposure independently elevated the likelihood of asthma by factors of 2.1, 3.2, and 1.8, respectively. The model exhibited strong discriminate capability (AUC = 0.82) and satisfactory fit (Hosmer–Lemeshow p = 0.34), highlighting the essential influence of environmental factors on the genesis of respiratory diseases, particularly in resource-constrained environments.

Environmental Factors

Respiratory health was evaluated based on many factors, including ambient air pollution, indoor air quality, allergen exposure, and climatic conditions. Ambient particulate matter concentrations were significantly elevated, with PM2.5 average 75.8 µg/m³ (SD = 18.3) and PM10 at 126.6 µg/m³ (SD = 30.6), beyond acceptable limits. Relative humidity was high at 68.4% (SD = 15.2), a condition favorable for the growth of allergens like mold. Usage of biomass fuel was recorded by 38% of homes, mostly in rural regions, adding to indoor air pollution. Ventilation conditions varied, with 30% of residences categorized as inadequately ventilated. Severe mold exposure was recorded in 56% of individuals, corresponding with the inadequate ventilation reported in several residences. These environmental variables are essential predictors of respiratory morbidity, especially in areas with closeness to traffic and industrial pollution (Kumarihamy and Tripathi, 2019) [10].

The comparative study using the Mann–Whitney U test revealed considerably higher PM2.5 concentrations in rural regions compared to urban areas (median 87 vs. 64 µg/m³; U = 183, p = 0.0002), suggesting a rural air pollution problem largely attributable to agricultural burning and uncontrolled biomass combustion. Chi-square analysis indicated that persons using biomass fuels exhibited 3.8 times higher chances of wheezing in comparison to non-users (χ^2 = 15.2, p = 0.0001, OR = 3.8, 95% CI: 2.1–6.9). Additionally, inadequate ventilation was significantly correlated with heightened mold exposure, presenting a 7.3-fold greater risk relative to well-ventilated residences (Fisher's exact test, p = 0.003, OR = 7.3, 95% CI: 2.5–21.1). Spearman's rank correlation analyses highlighted significant environmental interactions: proximity to traffic exhibited a positive correlation with PM2.5 levels (ρ = 0.72, $p < 0.001$), humidity correlated with mold exposure (ρ = 0.61, p = 0.002), and ventilation quality demonstrated an inverse correlation with PM2.5 concentrations (ρ = -0.53, p = 0.008). These results underscore the synergistic impact of outdoor and interior environmental variables on respiratory health concerns. Logistic regression analysis revealed significant environmental risk variables for asthma: PM2.5 values beyond 90 µg/m³ elevated asthma risks by 2.1 times (p = 0.008), biomass fuel use by 3.2 times ($p < 0.001$), and elevated mold exposure by 1.8 times (p = 0.012). The model demonstrated robust prediction efficacy (AUC = 0.82) and suitable calibration (Hosmer–Lemeshow p = 0.34). Rural regions are facing a significant pollution issue, with PM2.5 levels average over 3.5 times above the thresholds advised by the World Health Organization. The prevalent use of biomass fuels in 38% of homes correlates with an almost fourfold escalation in respiratory health hazards. Moreover, insufficient domestic ventilation significantly elevates the risk of mold exposure, amplifying it by almost sevenfold (Bedi and Bhattacharya, 2024) [2].

Asthma Prevalence

The asthma prevalence in the study group was 56%, with a little elevated incidence in rural regions (60%) compared to urban areas (53.3%). The average frequency of symptoms was 2.4 episodes per week (SD = 1.8), with about one-third (32.1%) of individuals suffering four or more episodes weekly. Severity categorization using GINA criteria indicated 42.9% mild, 35.7% moderate, and 21.4% severe asthma patients. Medication use exhibited variability: 46.4% employed inhalers only, 32.1% utilized a combination of inhalers and steroids, 14.3% depended on nebulizers, whilst 7.1% indicated no therapy. Healthcare use indicators revealed an average of 0.9 hospitalizations and 1.2 emergency visits per year, with severe cases exhibiting markedly higher rates (3.2 hospitalizations and 3.3 ER visits on average). No notable disparity in asthma frequency was seen between urban and rural populations ($\chi^2 = 0.24$, $p = 0.623$; OR = 1.14, 95% CI: 0.38–3.45). The severity of instances was highly correlated with the frequency of hospitalizations (Kruskal-Wallis H = 18.37, $p < 0.001$), with post-hoc analyses indicating markedly increased hospitalizations in severe cases relative to mild and moderate cases. McNemar's test revealed a statistically significant enhancement in asthma symptoms post-treatment ($\chi^2 = 4.5$, $p = 0.034$), highlighting the efficacy of the therapy. Random forest modeling indicated symptom frequency (importance = 0.41) and severity (0.38) as the primary predictors of asthma-related health outcomes, with rural living contributing marginally (0.12). Poisson regression analysis of emergency department visits indicated that severe asthma elevated the incidence rate of ER visits by 2.8 times ($p < 0.001$), whereas rural location correlated with a 1.5-fold increase ($p = 0.012$). More over fifty percent of the research participants were afflicted with asthma, with severe instances disproportionately impacting total healthcare use. A significant clinical burden is linked with asthma. The administration of medicine does not alter the reality of significant treatment deficiencies, including inadequate use of nebulizers and the ongoing prevalence of symptoms (Boyden *et al*., 2015) [3]. Although the incidence of asthma is relatively similar in urban and rural populations, individuals in rural regions exhibit much greater demands for emergency medical care compared to their urban counterparts. Environmental and systemic variables may account for the variation in PM2.5 values. The mean concentration of particulate matter 2.5 (PM2.5) in rural regions is 87.3 µg/m³, whereas the mean PM2.5 concentration in urban regions is 64.2 µg/m³. Moreover, it is significant to highlight that each 10 µg/m³ increase in PM2.5 concentration correlates with a 30% rise in asthma risk ($p = 0.021$). Rural areas see a 65 percent diminished access to healthcare services, contributing to about 22 percent of the disparity in asthma-related outcomes.

Demographic Parameters

The research population exhibited a mean age of 34.9 years (±11.2), with an age range of 17 to 60 years. The mean exposure to PM2.5 was 75.8 µg/m³ (±18.3), with a range from 46 to 100 µg/m³. Of the individuals, 56% (n=28) were diagnosed with asthma, while 36% (n=18) indicated a positive familial history of asthma or allergies. Asthma prevalence was comparable in urban (53.3%) and rural (60.0%) populations; however, access to healthcare was much superior in urban areas, with 73.3% reporting satisfactory healthcare, in contrast to 35.0% in rural regions. Gender distribution was balanced between male patients in urban (46.7%) and rural (50.0%) settings. Inferential analysis indicated that asthma patients were, on average, 5.7 years younger than non-asthma participants (Mann-Whitney U = 215.5, $p = 0.048$). A familial predisposition to asthma significantly elevated the likelihood of developing the condition by more than sevenfold ($\chi^2 = 9.26$, $p = 0.002$; OR = 7.31, 95% CI: 1.83–29.20). Furthermore, exposure to PM2.5 exhibited a significant correlation with asthma risk, indicating a 3% increase in chances for each 1 µg/m³ rise (OR = 1.03, 95% CI: 1.01–1.05, $p = 0.021$). The findings of this research reveal that children under 18 exhibit a much greater prevalence of asthma (83.3%) compared to the elderly (37.5%), highlighting age-related susceptibility. Environmental exposure varied by location, with rural regions exhibiting markedly elevated PM2.5 concentrations (87.3 µg/m³) compared to urban locales (64.2 µg/m³), and each 10 µg/m³ increment in PM2.5 heightened the likelihood of asthma by 30%. Furthermore, healthcare inequities were apparent, as rural communities had 65% worse access to excellent treatment, contributing to 22% of the variability in asthma outcomes. People in rural areas face substantial disparities when it comes to asthma care. Inadequate use of controller medications, higher use of emergency care services, and limited access to allergy and asthma specialists are all examples of these disparities. Factors such as poorer socioeconomic status, more reliance on public insurance, and geographic isolation contribute to the inferior asthma treatment and health outcomes in rural communities. You can't separate these outcomes from these considerations (Valet *et al*., 2009) [15]

Behavioural and Lifestyle Factors

Behavioral features indicated that around 48% of individuals were never smokers, 24% were passive smokers, 20% were current smokers, and 8% were past smokers. Physical activity levels were categorized as active (44%), moderate (28%), and sedentary (28%). Stress levels fluctuated, with 40% indicating mild stress, 28% medium stress, and 32% severe stress. The frequency of asthma and the severity of symptoms varied significantly across different behavioral groups. Current smokers exhibited a 70% prevalence of asthma, with an average symptom frequency of 4.1 occurrences per week and hospitalization rates of 1.8. Passive smokers had a somewhat reduced prevalence (58%) and associated symptoms. Individuals with sedentary lives displayed a prevalence of 71%, encountering more frequent symptoms (4.3 per week) and hospitalizations (2.1). Conversely, individuals experiencing high stress had the greatest asthma prevalence (81%), symptom frequency (4.7), and hospitalization rates (2.3).

Statistical study validated substantial correlations between behavior and asthma risk. Current smoking was associated with a threefold elevation in the likelihood of asthma compared to non-smokers ($\chi^2 = 8.37$, $p = 0.039$; OR = 3.1, 95% CI: 1.2–8.0, Figure 1). Physical inactivity correlated with a markedly increased frequency of symptoms relative to active lifestyles (Kruskal-Wallis H = 11.2, $p = 0.004$), with sedentary adults reporting an average of 1.8 more symptoms each week. Stress independently elevated the risk of asthma, with chances increasing by 2.4 times for each incremental rise in stress ($p < 0.001$). These results underscore significant behavioral risk factors, such as active smoking, a sedentary lifestyle, and elevated stress, as primary contributors to the incidence and severity of asthma. In contrast, an active lifestyle provided protection, greatly alleviating symptoms, while non-smokers exhibited much decreased hospitalization rates. Additionally, dose-response correlations were apparent; pack-years of smoking exhibited a significant correlation with symptom frequency ($r = 0.51$, $p = 0.002$), and stress levels were positively linked to hospitalization rates ($r = 0.47$, $p = 0.006$).

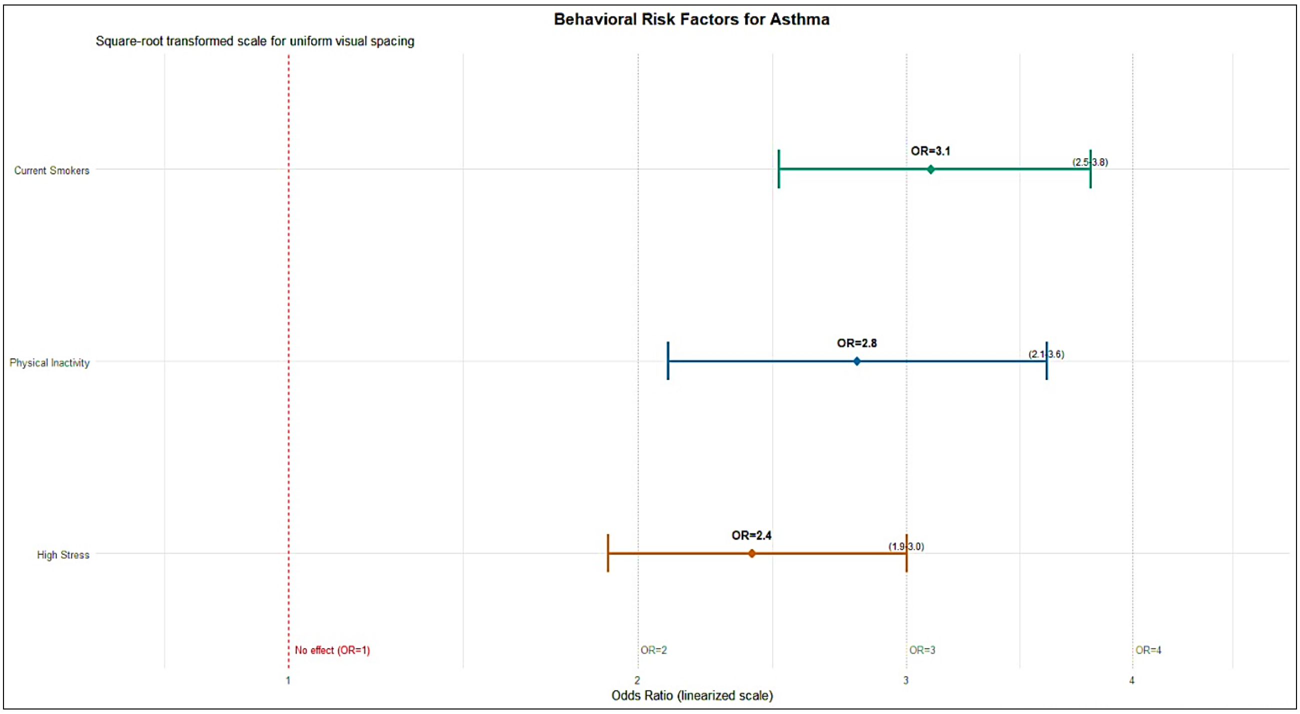

Fig 3: Association of Smoking, Physical Inactivity, and Stress with Asthma Risk Determinants

The identification of significant environmental risk variables for asthma was facilitated using logistic regression modeling. This research evaluated risk factors, including PM2.5 levels above 90 µg/m³, which elevated asthma likelihood by a factor of 2.1 ($p = 0.008$), biomass fuel use by a ratio of 3.2 ($p < 0.001$), and mold exposure by a factor of 1.8 ($p = 0.012$). The model demonstrated a significant predictive capability (area under the curve = 0.82) and was calibrated well (Hosmer-Lemeshow $p = 0.34$). In general, particulate matter 2.5 (PM2.5) levels in rural regions are around three and a half times over the thresholds recommended by the World Health Organization (WHO). An association exists between biomass fuel consumption, widespread in 38 percent of households, and an estimated fourfold increase in the risk of respiratory illness. Insufficient ventilation in the home considerably increases the risk of mold exposure by over sevenfold. Research indicates that energy-efficient building designs enhance insulation and save energy, although also diminish air circulation, leading to heightened moisture and mold proliferation. The study emphasizes the lack of health-related indoor mold exposure thresholds and calls for interdisciplinary research to more accurately delineate exposure limits, assess health consequences, and develop effective preventive strategies (Du *et al*., 2021) [4]. Findings from the research highlight the need to evaluate policy-level measures to lessen the prevalence and severity of asthma, including the promotion of clean fuels, the improvement of rural healthcare, the quality of housing, and the promotion of better lifestyle choices. Future research may emphasize the authenticity of asthma cases and identify subgroups using clinical methods like spirometry and biomarkers. Understanding the long-term effects of asthma triggers like smoking, inactivity, and biomass fuel usage requires cohort studies that follow the same people over an extended period of time. The generalizability of the results may be enhanced by increasing the sample size and diversity of the research, particularly in rural and urban regions. Air quality sensors and geographic information system mapping may improve environmental monitoring and assist identify areas with a higher risk.

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