

Multi-scale social-economic-environmental inequities lead to heterogeneity of Developmental Coordination Disorder risk across China

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Dear Editor,

Developmental Coordination Disorder (DCD) is a neurodevelopmental condition that significantly affects the physical and mental health of children, with a prevalence rate of 5–6% among the pediatric population. DCD frequently co-occurs with other neurodevelopmental disorders: approximately 79% of individuals diagnosed with Autism Spectrum Disorder (ASD) and 30–50% of those with Attention Deficit Hyperactivity Disorder (ADHD) also exhibit DCD symptoms. Despite its high prevalence, there is limited understanding of how socio-economic and environmental factors contribute to DCD. In this study, we analyzed data from over 90,000 children aged 3–5 years in China. We employed a dual-model approach combining Causal Bayesian Network (CBN) and Geographical Detector (GD) methods to identify DCD risk factors at both individual and city levels. At the individual level, family-related factors, particularly maternal education, and the availability of neighborhood green spaces were strongly associated with DCD. At the city level, broader factors such as green spaces, healthcare resources, regional GDP, and general education levels significantly influenced DCD risk. Interestingly, air pollution was not significantly associated with DCD risk at either level. These findings highlight the importance of supportive family environments and accessible green spaces in reducing DCD risk, offering valuable insights for preventive strategies.

STUDY POPULATION AND DESIGN

This study analyzed data from the Chinese National Cohort of Motor Development (CNCMD), encompassing 163 prefecture-level cities in China (Figure 1A). Motor skills were assessed using the Little Developmental Coordination Disorder Questionnaire (LDCDQ). The LDCDQ comprises three subscales evaluating movement control, fine motor skills, and overall coordination, each with five items. Parents rated their child's motor abilities compared to age- and sex-matched peers on a one ('not at all significant') to five ('very relevant') scale, where higher scores indicate superior motor proficiency and a reduced risk of DCD. The Chinese adaptation of the LDCDQ demonstrates robust conceptual validity, split-half reliability, and satisfactory construct validity. Using established guidelines,^{1,2} age- and sex-adjusted norms identified potential motor coordination challenges, classifying children below the 15th percentile as suspected DCD and those above as likely non-DCD. Detailed methodologies and questionnaire information are elaborated in previous publications.³ Parental consent was obtained in writing at enrolment, in compliance with the ethical standards sanctioned by the Institutional Review Board of Shanghai First Maternity and Infant Hospital (KS18156).

INDEPENDENT VARIABLES

The analysis examined a diversity of socio-economic and environmental factors influencing DCD incidence. At the individual level, we considered

family dynamics (e.g. parental ages at pregnancy, employment, education, income, marital status, household structure), children's physical activity (total practice hours for specific activity types on school days and weekends), and urban environmental factors (airborne pollutant exposure and access to green spaces). Daily pollutant data (10 km spatial resolution; 1 km for PM_{2.5}), were sourced from a public database (https://weijing-rs.github.io/product_cn.html), while green space availability was assessed using Normalized Difference Vegetation Index (NDVI) from another database (<https://www.resdc.cn/Default.aspx>). Individual exposure to NDVI and pollutants was mapped to participants' residential locations. We also differentiated the effects of pollutants during pregnancy and childhood by calculating average exposure levels according to birth and questionnaire completion dates.

At the city level, to understand regional disparities of DCD, we matched average DCD rates for each prefecture-level city with data from the China Urban Statistical Yearbook, including metrics like GDP, per capita income, public budget, education spending, green spaces, and number of parks and hospitals.

METHODS

Quantifying the influence of social-economic-environmental factors on DCD at the individual level based on Causal Bayesian Network

The Causal Bayesian Network (CBN) combines expert knowledge and observational data to infer causal relationships between the target variable and other factors using the causal diagram and Bayesian theory.⁴ CBN comprises a causal graph G and global probability distribution $P(V)$. The causal graph, a directed acyclic graph with variables $V = \{v_1, v_2, \dots, v_p\}$ and directed edges $E = \{e_1, e_2, \dots, e_m\}$, links parent (cause) nodes to child (effect) nodes. $P(V)$ represents the probability distributions of all variables in G and can be factorized into local conditional distribution functions as shown in formula (1),

$$P(v_i) = \prod_{v \in V} P(v_i | Pa(v_i)) \quad (1)$$

Where v_i 's parent node is $Pa(v_i)$. In CBN, cause variables predict the effect variable through functional relationships f in formula (2) while G explains their interactions.

$$v_i := f(Pa(v_i)) \quad \forall v_i \in V \quad (2)$$

CBN performs causal inference in two steps. First, priori expert knowledge establishes a preliminary graph, designating known causal associations as a white list and excluding impossible ones as the black list. Then, observational data updates the graph using constraint-based, score-based, or directional assumptions functions. Finally, functional relationships between cause and effect variables are estimated using maximum-likelihood strategy. CBN are able to capture the direct and indirect effects of multiple factors on DCD risk and quantify these effects through probabilities, providing us with are

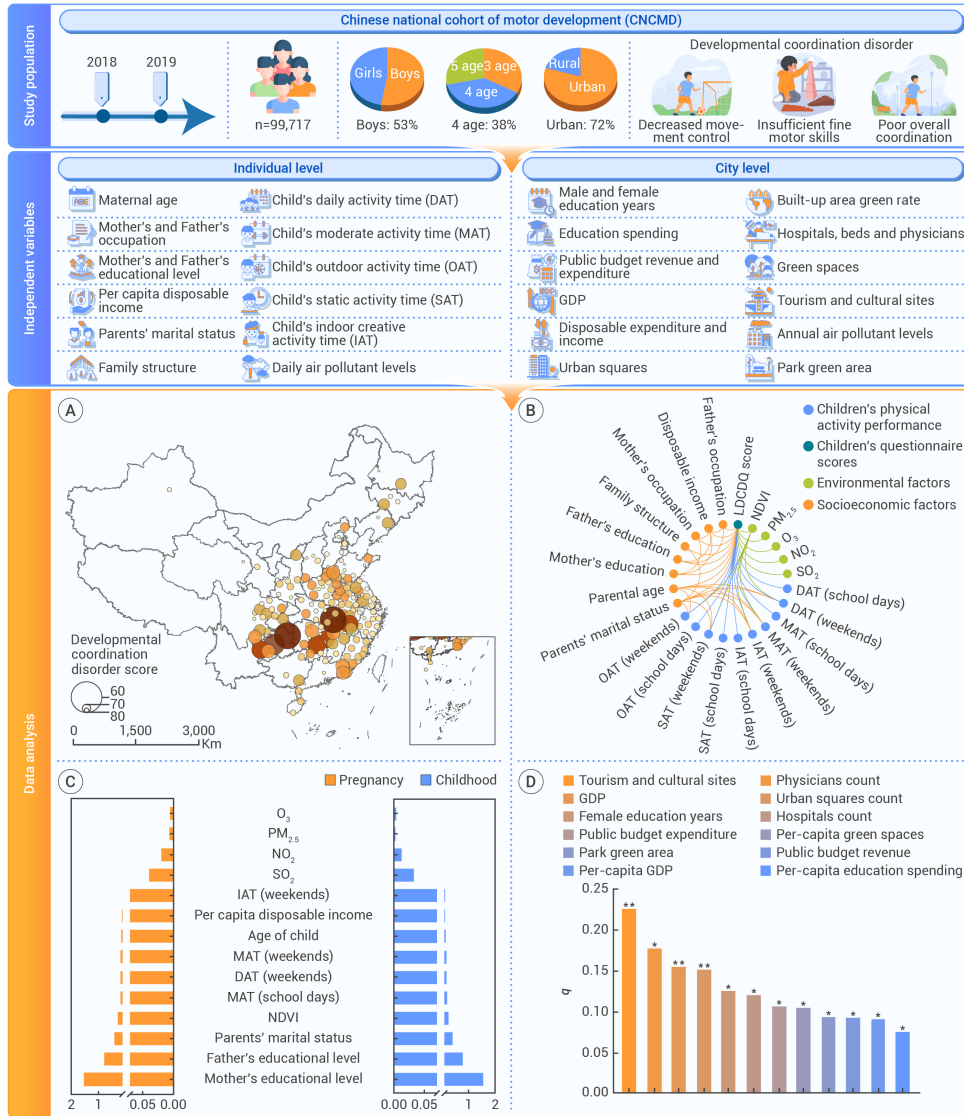


Figure 1. Study population, independent variables and causal-analysis outputs (A) National distribution of mean DCD Score at the city level. (B) Causal Bayesian Network. (C) Causal Bayesian Network outputs. NDVI= Normalized Difference Vegetation Index. The larger the β coefficient, the stronger the association between the factor and DCD is. (D) GD Outputs of individual factors on DCD. GDP=Gross Domestic Product. The larger the q value, the stronger the association between the factor and DCD is. The bar graph excluded the factors that did not pass the test of significance. Asterisk denotes statistically significant differences, ** $p < 0.01$; * $p < 0.05$.

nancy and childhood (Figure 1C). Although β does not directly stand for the quantitative influence, the magnitude and ranking of these β coefficients suggests the relative importance of each social-economic-environmental factors.

Maternal education emerged as the most influential factor ($\beta > 1.5$), nearly double that of paternal education ($\beta > 0.75$). Marital status followed ($\beta > 0.4$), along with environmental factors represented by NDVI ($\beta > 0.25$). Children's activity-related variables, including location, intensity, and type, also showed a strong correlation with DCD (β between 0.10 and 0.20). Unexpectedly, airborne pollutants had the smallest influence ($\beta < 0.04$).

Children of mothers with a college degree or higher had significantly lower DCD risk, with an exemption rate of 88.87%, compared to 77.23% for children of mothers without higher education. Similarly, children of fathers with college degrees was 88.0%, versus 78.0% for those without. Parental marital status also strongly affected DCD outcomes. Specifically, children of married parents had an exemption rate of 84.18%, compared to 78.17% for those of separated parents.

liable tool for inference and quantification.

Quantifying the influence of social-economic-environmental factors on DCD at the city level based on Geographical Detector

Geographical Detector (GD)⁵ is a statistical tool used to detect spatial differences and their underlying causes by assessing the consistency in spatial distribution between dependent and independent variables. Due to its capability of capturing associations across geographical locations, GD is widely applied in disease and health research, providing insights into spatial aspects of health phenomena. GD outputs majorly include a quantitative q statistic, as shown in formula (3).

$$q = 1 - \frac{\sum_{h=1}^H N_h \sigma_h^2}{N \sigma^2} \quad (3)$$

The formula divides variable Y or factor X into stratum H . N represents the total study areas. Y variance in stratum h is σ_h^2 and overall variance as σ^2 . The non-central F distribution determines q significance.

GD's spatial analysis reveals and quantifies regional differences in DCD risk factors, assisting the analysis of the impact of socioeconomic and environmental factors, making it ideal for urban risk assessment.

RESULTS

Major influencing factors on DCD at the individual level

Using the CBN model, we established a multi-factor framework for DCD risk (Figure 1B) and calculated the β value for various factors during preg-

Major influencing factors on DCD at the city level

To minimize uncertainties from annual variations, we examined the three-year average (2016-2018) of city-level variables on averaged DCD scores and excluded cities with fewer than five records. The strength of association between each factor and DCD score was quantified by q -values, with higher q -values indicating stronger associations. The key drivers of DCD included the availability of green spaces and entertainment, medical resources, economic factors, and educational conditions. The major influencing factors for each category were as follows (Figure 1D). Green spaces and entertainment: tourism and cultural sites (q 0.228, sig 0.01), urban squares count (q 0.153, sig 0.01), per-capita green spaces (q 0.107, sig 0.046) and park green area (q 0.096, sig 0.045). Medical resources: physicians count (q 0.178, sig 0.05) and hospitals count (q 0.122, sig 0.044). Economic factors: GDP (q 0.157, sig 0.025), public budget expenditure (q 0.11, sig 0.038), public budget revenue (q 0.095, sig 0.038) and per-capita GDP (q 0.094, sig 0.035). Educational conditions: females education years (q 0.128, sig 0.039) and per-capita education spending (q 0.078, sig 0.026). No significant associations were found between city-level airborne pollutants and DCD. In summary, economic conditions, medical resources and infrastructure strongly influenced the average DCD incidence rate in cities. Rural areas (18.5%) had a higher DCD incidence rate than urban areas (15.6%).

Geographical Detector revealed strong interactions between factors affecting DCD, including combinations of green spaces with education spending (q 0.623), hospitals with tourism sites (q 0.608), green spaces with physicians (q 0.564), and green spaces with tourism sites (q 0.550). These outputs identified green spaces, medical resources, and educational as key factors for DCD

and suggested that combined improvements in these areas could significantly reduce urban DCD risk.

PERSPECTIVES

Despite a large size of sampling and a diversity of influencing factors comprehensively considered, some limitations remain. For this cohort survey, children with severe visual, hearing, or intellectual disabilities were excluded and we majorly focused on those in mainstream kindergartens. While this ensured data quality, it may have introduced selection bias, limiting generalizability and underestimating DCD prevalence in a broader population. Children from special education schools could be included in future research to reduce sampling bias. Additionally, potential confounders genetic factors, perinatal health status, and heavy metal pollution were not included due to the lack of relevant data sources. Considering the difficulty of acquiring such data sources, small-scale studies can be conducted to explore their effects on DCD risk.

The ranking of social-economic-environmental factors provides new insights into DCD risks. Unlike traditional public health findings focusing on airborne pollutants,⁶ we found that DCD risk is more strongly influenced by factors such as parental education, particularly maternal education, marital stability, urban infrastructure, and access to green spaces. Educated parents are more likely to prioritize physical activities for children's health,^{7,8} particularly mothers in China, making maternal education a key factor. Environmental factors like NDVI, as easy access to green spaces significantly impacts the frequency, duration and intensity of children's physical practice, thereby influencing DCD risk. Family income affects living conditions, diet and overall health.⁹ At the city level, green spaces and attractions and medical resources promote outdoor activities and early intervention. Regional GDP, government budgets, and city education levels shape infrastructure and health resources, influencing DCD risk and incidence.

Children of college-educated parents have a higher exemption rate from DCD (88%) compared to those with non-college-educated parents (78%). Parents can guide children's physical and mental activities through books or courses and by engaging in regular activities together. This research also highlights the importance of joint parental involvement, especially for separated parents. Policymakers should ensure equitable access to green spaces and invest in medical resources, particularly in rural areas, for early DCD diagnosis. Raising public awareness through seminars and improving both green spaces and medical conditions together can significantly reduce DCD risk.

This research uses of Causal Bayesian Network (CBN) to identify family factors as key drivers of DCD risk, offering more robust insights than traditional models like correlation analysis and regression. CBN effectively uncovers major contributors to disease from various socio-economic and environmental factors. Pointing out that DCD risk is not just an individual issue but is shaped by social and environmental factors, offering policymakers new perspectives for designing interventions.

Additionally, this study uniquely examines DCD risk factors at both the individual and city scale, providing a comprehensive multi-scale attribution approach that enables cross-verification of factors, which single-scale analysis cannot achieve. Combining CBN with Geographical Detector (GD), this approach offers a comprehensive perspective and is recommended for studying other diseases. These findings advocate for targeted policies to enhance education, healthcare, and urban planning, fostering healthier environments that support child development and advance public health. This study enhances understanding of DCD risk factors in large populations and identifies key areas for targeted intervention in high-risk groups, with signifi-

cant public health implications. Our findings will positively impact China's health policy, education, and social support systems.

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AUTHOR CONTRIBUTIONS

Z.C., J.Y., B.G., W.C.D., and J.H. conceptualized the study, contributed to the investigation, obtaining funding, and software coding. Z.C., J.Y. and B.G. contributed to the methodology. J.Y., X.C. and C.Z. did the formal analysis, and data curation. Z.C., J.Y., W.C.D. and J.H. accessed and verified the underlying data. Z.C., J.Y. and W.C.D. wrote the original draft of the manuscript. Z.C., Z.F., W.C.D., M.L. and W.H.D. reviewed and edited the manuscript. Z.C. supervised, acquired funding, and did project administration. J.Y., contributed to creating the figures. All authors had full access to all the data in the study and had final responsibility for the decision to submit for publication.

DECLARATION OF INTERESTS

The authors declare no competing interests.

ETHICAL STATEMENT AND PATIENT CONSENT

Parental consent was obtained in writing at enrolment, in compliance with the ethical standards sanctioned by the Institutional Review Board of Shanghai First Maternity and Infant Hospital (KS18156).

DATA AND CODE AVAILABILITY

Daily pollutant data (10 km spatial resolution; 1 km for PM_{2.5}), were sourced from a public database (https://weijing-rs.github.io/product_cn.html), while green space availability was assessed using Normalized Difference Vegetation Index (NDVI) from another database (<https://www.resdc.cn/Default.aspx>).