Air Quality, Atmosphere & Health (2026) 19:159
https://doi.org/10.1007/s11869-026-02041-1

Green economy and artificial intelligence: pathways to better air quality and health in China

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Received: 28 November 2025 / Accepted: 16 June 2026

Abstract
China is under growing pressure from rising healthcare costs, persistent air-pollution exposure, rapid urbanization, and fast digital transformation. While previous studies have examined how pollution, energy production, and technological change affect health expenditure, most rely on average-based methods that overlook how these relationships differ when healthcare spending is low, moderate, or high. This study addresses that gap by treating health expenditure as a nonlinear, distribution-sensitive outcome shaped by artificial intelligence, green growth, energy production, and air quality. The study applies quantile ADF and quantile KPSS stationarity tests, and multivariate quantile-on-quantile regression, with conventional quantile regression used for robustness. The findings show clear nonlinear patterns, stable conditional distributions, and strong quantile-specific differences. Artificial intelligence has a mixed effect: it may increase spending through digital infrastructure and diagnostic investment, but may also reduce cost pressure through efficiency, early detection, and better resource allocation. For long-term policy, China's health expenditure reflects a complex technology–energy–environment nexus, requiring coordinated policies on AI, green growth, clean energy, urban planning, and air quality improvement.

Keywords Artificial intelligence; Green economy · Health · Air quality · China · MQQR

Background

Ambient air pollution is a major public health concern across the world. In 2019, the World Health Organization estimated that outdoor air pollution was linked to more than 4.2 million premature deaths globally. Evidence from epidemiological studies continues to show that exposure to fine particulate matter, especially PM2.5, is associated with a higher risk of cardiovascular and respiratory diseases, lung cancer, and premature death (Wang et al. 2026). The effects are not limited to health alone. PM2.5 pollution also places a heavy economic burden on societies by increasing health care costs, raising hospital admission rates, and reducing workforce productivity through illness and early mortality (Global Health 2022). These consequences are felt most strongly in low- and middle-income countries, which are home to about 80% of people exposed to unsafe annual PM2.5 concentrations and account for nearly 90% of premature deaths related to air pollution (Rentschler and Leonova 2023). To address this growing burden, many countries have introduced policies aimed at lowering particulate pollution. In Southeast Asia, Indonesia, Vietnam, and Thailand have adopted measures such as national air quality standards, emission controls in transport, industry, and energy, and stronger air monitoring networks to reduce emissions and limit public exposure (Lukman et al. 2025). India offers another important example through its National Clean Air Program, which has been linked to noticeable reductions in PM10 levels across 20 major cities and was estimated to have prevented about 62,219 excess deaths in 2021 compared with 2018 (Gopikrishnan and Kuttippurath 2025).

Over the past decade, China have introduced a broad range of policies to address PM2.5 pollution. The first phase, from 2013 to 2017, was guided by the Air Pollution Prevention and Control Action Plan and focused largely on end-of-pipe controls, cleaner fuels, and technological upgrades in the power and heavy industrial sectors. These measures

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led to substantial reductions in emissions and clear declines in PM2.5 concentrations. The second phase, implemented from 2018 to 2020 under the Blue Sky initiative, placed greater emphasis on structural change and coordinated control of multiple pollutants. Alongside particulate matter, stronger regulatory attention was given to NOx, VOCs, and NH3 (Li et al. 2024).

Although the concept of a green economy emerged in the early 1970s, it gained renewed attention around 2009, when international organizations called on donors and policymakers to align economic strategies with sustainability goals, reduce carbon-intensive investments, and expand renewable energy portfolios (Zaman et al. 2016). Following this global push, China began prioritizing green growth and reducing the carbon intensity of its economic activities. Facing severe environmental challenges while sustaining rapid economic growth, the Chinese government has liberalized trade policies and opened investment channels for environmental and clean energy projects (Raihan et al. 2023). This approach complements China's broader air quality initiatives, including the Air Pollution Prevention and Control Action Plan and the Blue Sky initiative, which targeted PM2.5 and other pollutants. Together, these efforts demonstrate how integrating green economy strategies with pollution reduction policies can protect public health, promote sustainable industrial growth, and support long-term environmental resilience. The objective of this study is to examine how energy consumption, environmental degradation, and health indicators influence China's green growth trajectory, providing insights for policymakers on effective strategies for sustainable development and clean energy investment.

Artificial intelligence is becoming an integral part of environmental health management, especially in contexts of air quality and sustainable economic transformation. In environmental monitoring, AI systems enhance the precision and timeliness of air pollution surveillance by integrating large environmental datasets and identifying patterns of pollutant dispersion that are challenging for conventional approaches to capture (Li and Lu 2026). These capabilities improve exposure assessment for fine particulate matter such as PM2.5, which is strongly linked to cardiovascular, respiratory, and other adverse health outcomes, allowing health systems to anticipate stress on services and target interventions more effectively. AI also contributes to public health by supporting predictive models that forecast high-risk pollution episodes, enabling proactive health advisories and resource planning (Godoy Junior et al. 2026). Beyond direct health monitoring, AI stimulates technological innovation that underpins green economic strategies, such as optimizing energy systems, reducing inefficiencies in industrial processes, and guiding policy instruments that reduce emissions at source. Studies in China and other urban economies have shown that integrating AI into environmental governance frameworks is associated with improved air quality outcomes and supports transitions toward cleaner energy and lower pollution pathways, which in turn reduces disease burden and health care costs while reinforcing the objectives of a green economy (Nzazi et al. 2025). This linkage illustrates that AI-driven tools can align environmental protection, economic development, and population health objectives when deployed with clear policy guidance and cross-sector collaboration.

Energy production sits at the core of modern economic activity, but its methods and efficiency have direct consequences for public health, environmental sustainability, and economic growth (Aydin et al. 2024). Traditional energy production, particularly from coal, oil, and other fossil fuels, emits large quantities of air pollutants, including fine particulate matter (PM2.5), nitrogen oxides, and sulfur dioxide (Ma et al. 2023). Chronic exposure to these pollutants increases the incidence of cardiovascular and respiratory diseases, lung cancer, and other health conditions, which in turn elevates health care expenditures through hospital admissions, long-term treatments, and lost workforce productivity. Economically, the burden is substantial: higher energy-related pollution translates to higher societal costs and diverts resources from other developmental priorities (Aydin et al. 2024).

Artificial intelligence offers transformative potential in this context. By optimizing energy generation, distribution, and consumption, AI can significantly reduce emissions from power plants and industrial facilities. Predictive maintenance algorithms, real-time grid management, and demand forecasting reduce inefficiencies and limit pollutant release, directly decreasing the health impacts of energy production (Godoy Junior et al. 2026). Moreover, AI supports the transition to renewable energy sources by improving integration of solar, wind, and other clean energy into power grids, maximizing output and minimizing curtailment. These AI-driven efficiencies lower the marginal cost of energy production while simultaneously reducing public health risks, effectively aligning economic incentives with environmental and health outcomes.

This connection between energy, health, and technology feeds directly into green growth strategies. By coupling cleaner energy production with AI-enabled management and policy enforcement, countries can simultaneously reduce carbon intensity, improve air quality, and limit health care expenditures (Uche and Odhiambo 2026). Green growth is therefore not only an environmental imperative but an economic and public health strategy: cleaner energy reduces pollution-related disease burdens, which decreases health expenditures, while AI accelerates the deployment of low-carbon technologies and enhances the efficiency of industrial and energy sectors (Nica et al. 2023). This creates a reinforcing loop in which technology, health, and sustainable development are mutually supportive, illustrating that the future of energy production must be digitally intelligent, environmentally responsible, and health-conscious to achieve truly sustainable growth.

Contribution

This study contributes to the literature in three main ways. First, it brings green growth into the discussion on health expenditure, a relationship that has received very limited direct empirical attention. Most previous studies have focused on how economic growth, environmental pollution, CO_2 emissions, energy use, or general health indicators influence healthcare spending, but the connection between health expenditure and green growth remains underexplored. By including green growth, this study adds a sustainability-focused perspective and shows how environmentally responsible development may shape healthcare financing in China. Second, the study adds to the growing literature on artificial intelligence and health economics by examining how AI affects health expenditure using annual country-level data for China. Although some studies have discussed AI in relation to healthcare systems, innovation, education, and economic development, there is still limited empirical evidence on whether AI raises health spending through investment in digital infrastructure or helps reduce expenditure pressures through better diagnosis, improved efficiency, resource optimization, and preventive healthcare. This is particularly important for China, where AI development, healthcare reform, urbanization, and environmental governance are advancing rapidly. Third, the study makes a methodological contribution by using quantile unit root tests and multivariate quantile-on-quantile regression rather than relying only on conventional mean-based approaches. This method allows the analysis to capture nonlinear, asymmetric, and distribution-specific relationships among health expenditure, AI, green growth, economic growth, energy production, urbanization, and air quality. In this way, the study does more than show whether these factors influence health expenditure; it also explains how their effects change across low, middle, and high levels of health spending, offering more detailed and policy-relevant insights for China's healthcare financing and sustainable development strategy. Figure 1 indicated structure of the study as follow.

Literature review

Green growth with health expenditure

Dritsaki and Dritsaki (2023) investigated the relationship between per capita health expenditure, CO_2 emissions, and GDP in G7 countries using heterogeneous panel data. They found that GDP positively influences health spending, while CO_2 emissions have a negative long-run effect, and causality runs unidirectionally from emissions to health expenditure, highlighting the impact of environmental pressures on healthcare costs. Higher public health spending

Fig. 1 Shows structure of the study

and the share of current health expenditures in GDP positively affect GDP and per capita income in OECD countries, whereas increases in out-of-pocket spending have mixed effects, highlighting the role of public health investment in promoting economic growth (Beylik et al. 2022). In G7 countries, life expectancy and public health expenditure are the strongest drivers of long-run economic growth, while environmental quality also contributes significantly. The study highlights pronounced asymmetric effects, with positive shocks in health indicators yielding greater economic benefits than negative shocks. These findings emphasize the importance of sustained investment in health and the environment for resilient and inclusive growth (Dar et al. 2025). Wang et al., (2019) found that in Pakistan, CO_2 emissions, health expenditures, and economic growth are dynamically linked, with significant long-run and short-run causal relationships. Bidirectional causality exists between health spending and both CO_2 emissions and economic growth, while short-run causality runs from emissions to health expenditures. The study highlights the need for policies that manage pollution and healthcare spending without undermining economic growth. Yahaya et al. (2016) show that environmental quality is a key determinant of per capita health expenditures in developing countries. Their panel analysis of 125 countries from 1995–2012 finds that CO_2 emissions have the strongest long-run impact on health spending, highlighting the importance of clean air policies. The study recommends prioritizing environmental management to reduce healthcare costs and improve population health. This study examined the impact of environmental quality on public health expenditure in Malaysia using time-series data from 1970–2013. Their ARDL and cointegration analysis shows that GDP, CO_2, SO_2, NO_2, fertility rate, and infant mortality are significantly related to long-run health expenditure, with SO_2, fertility, and infant mortality exerting the strongest effects. The study highlights the role of environmental management and population health in sustaining national development (Abdullah et al. 2015). Existing studies have examined the relationship between health expenditure and economic growth, but none have considered its link with green growth. Most research focuses on panel or single-country analyses without integrating environmental sustainability. This gap highlights the need for empirical investigation of how health spending interacts with green growth to inform sustainable development policy.

Artificial intelligence with health expenditure

Health, education, artificial intelligence, and renewable energy are all found to significantly influence Morocco's long-term economic growth. The study highlights the interconnected role of human capital, technology, and green energy in promoting sustainable development. These findings underscore the importance of integrated policy planning to support inclusive and environmentally conscious economic growth, (Almusallam et al. 2025). Ageli (2026) finds that in GCC countries, life expectancy is influenced more by digital transformation and environmental efficiency than by the volume of health expenditures. Economic growth has a modest positive effect, while higher per capita carbon emissions reduce health outcomes. The study highlights the importance of integrating digitalization and environmental sustainability into public health strategies to improve population health. Artificial intelligence can serve as a sustainable and scalable alternative to traditional foreign aid in promoting education, health, and economic growth. Unlike conventional aid, which can create dependency and inefficiency, AI-driven interventions enhance local capacity, inclusivity, and ethical development. The study emphasizes AI's potential to support the achievement of sustainable development goals through culturally sensitive and participatory approaches (Lainjo 2025). Chhillar (2024) argues that artificial intelligence (AI) can strategically enhance health, education, and economic systems by improving diagnostic accuracy, optimizing healthcare delivery, enabling personalized learning, and supporting evidence-based policy planning. When combined with equitable governance and institutional capacity, AI serves as a key enabler of resilient social systems, adaptive learning environments, and inclusive economic transformation. Existing studies show that AI influences health, education, and economic outcomes, but none treat health expenditure as a dependent variable. Moreover, none apply Multivariate Quantile-on-Quantile Regression (MQQR) to capture heterogeneous and nonlinear effects across the distribution of health spending. This highlights a clear research gap in understanding how AI and related technologies affect public health financing.

Energy production and health expenditure

Yasin et al. (2024) show that in developing Asian economies, government health expenditure and energy consumption positively affect life expectancy, while higher ecological footprint reduces it. The study underscores the need for efficient health spending and sustainable energy production to improve population health outcomes. Raouf (2023) investigates the relationship between green hydrogen production and per capita public health expenditure in 67 hydrogen-exporting countries from 2000 to 2021. The study finds that increased hydrogen energy production raises health spending, both by reducing CO_2-related health risks and by generating export revenues that can fund public health. These results highlight the dual benefits of low-carbon energy production for environmental sustainability and enhanced health investment. Higher GDP and carbon emissions in 36 Asian countries are associated with increased healthcare expenditure, while renewable energy consumption helps reduce health costs. The study highlights the importance of promoting clean energy and efficient healthcare investment to achieve sustainable health services without compromising economic growth (Slathia et al. 2024). In Southeast Asia, greenhouse gas emissions and GDP are found to significantly influence health expenditure, while the effect of renewable energy consumption is model-dependent, showing significance only under quantile regression. The study also identifies both short- and long-run causal effects between GHG emissions, economic growth, and health spending. These findings emphasize the need for policies that integrate economic development, environmental management, and healthcare investment to promote sustainable health outcomes (Sangco 2024). Unhealthy behaviors and environmental risks significantly increase healthcare expenditure in European countries, and effective prevention can help sustain health financing (Zimmermannová et al. 2026). Energy production is rarely studied in relation to health expenditure, despite its impact on pollution and public health. Exploring this link can reveal how cleaner, low-carbon energy strategies influence healthcare demand and government health spending. This approach addresses a key research gap and informs policies for sustainable health and energy systems.

Health expenditure with air quality

China's clean air actions have significantly improved air quality, reducing hospitalization days and medical expenses for major air-pollution-related diseases, particularly benefiting low- and middle-income cities and those with limited healthcare resources. These measures not only lower overall health expenditures but also alleviate regional inequality in healthcare costs. However, the projected benefits may be partially offset by the demands of an aging population (Weng et al. 2023). In the United States, long-term exposure to air pollution significantly reduces life expectancy, while medical innovations positively contribute to longevity. Surprisingly, higher health expenditures and economic complexity do not necessarily improve life expectancy, highlighting inefficiencies in resource allocation. These findings underscore the need for targeted policy measures to mitigate air pollution and enhance the effectiveness of healthcare and economic interventions (Muradov et al. 2024). Guo and Liu (2024) find that air pollution in the Guangdong–Hong Kong–Macao Greater Bay Area significantly increases residents' health expenditures, with PM2.5 levels showing a strong positive association with per capita medical costs. The study also highlights spatial spillover effects, indicating that pollution in one area can exacerbate health spending in neighboring regions. Orset (2024)demonstrates that emissions of ammonia, arsenic, and cadmium from the transport sector in 15 EU countries significantly increase public health expenditures, with ammonia and cadmium affecting short-term costs and arsenic impacting long-term spending. The study emphasizes that early and stringent pollutant reduction policies can substantially lower per capita health expenditures, highlighting the economic benefits of environmental regulation. Despite extensive evidence linking air pollution to increased health expenditures and reduced life expectancy, the existing studies primarily employ mean-based or panel econometric approaches. None of the reviewed research investigates the heterogeneous effects of air pollution across the conditional distribution of health expenditures using a multivariate Quantile-on-Quantile regression framework. This methodological gap limits understanding of how different levels of pollution exposure may affect populations with varying healthcare cost burdens, leaving nuanced policy implications unexplored.

Literature review gap

Extant literature provides substantial evidence that air pollution, energy production, and environmental degradation significantly affect health expenditures and population health outcomes across countries and regions (Guo and Liu 2024; Muradov et al. 2024; Weng et al. 2023). Studies have also examined the roles of green growth policies, artificial intelligence, and renewable energy in moderating these health and economic effects, highlighting the links between sustainable development, technological innovation, and public health (Almusallam et al. 2025; Chhillar 2024; Dritsaki and Dritsaki 2023). However, the literature remains fragmented in three key ways: (1) most research relies on mean-based or panel regression models that fail to capture heterogeneity in health expenditure responses across different population groups or pollution levels; (2) there is limited integration of multivariate and nonlinear relationships among air quality, AI adoption, green growth, energy production, and healthcare costs; and (3) none of the existing studies employ advanced methodologies such as multivariate Quantile-on-Quantile regression to explore distribution-specific effects. These gaps constrain understanding of the nuanced, nonlinear, and conditional impacts of environmental and technological factors on health expenditures, leaving critical policy-relevant insights on equity, efficiency, and targeted interventions unexplored.

Theoretical framework

China has experienced rapid economic growth over the past decades, accompanied by rising health expenditures, increasing energy production, and growing investments in artificial intelligence (AI). These factors are critical in shaping sustainable development and green growth, as China seeks to balance economic expansion with environmental protection and population health. Understanding the interactions among health expenditure, green growth, AI, and energy production is essential for informing effective policy and promoting sustainable development in the Chinese context.

Health expenditure reflects a country's investment in the well-being of its population, influencing life expectancy, productivity, and human capital formation. In China, rising healthcare costs are driven by population aging, urbanization, and the prevalence of chronic diseases. Theoretically, higher health spending improves population health, reduces mortality, and enhances economic productivity, creating a feedback loop where healthier populations contribute to economic growth. Models of health economics suggest that both public and private expenditures are critical determinants of aggregate health outcomes.

Green growth integrates economic development with environmental sustainability, emphasizing low-carbon technologies, energy efficiency, and reduced ecological footprints. In China, green growth policies aim to mitigate pollution, conserve natural resources, and transition toward renewable energy. Theoretical models posit that environmental quality and sustainable resource use are not only ecological imperatives but also influence human health, innovation, and long-term economic productivity. By promoting green growth, governments can reduce health risks associated with pollution while maintaining economic expansion.

AI represents a transformative technology that enhances productivity, decision-making, and service delivery across multiple sectors. In healthcare, AI can improve diagnostics, optimize resource allocation, and support population health monitoring. In China, AI adoption is closely linked to digitalization strategies that boost innovation and economic efficiency. Theoretically, AI can amplify the impact of health expenditure by increasing the effectiveness of healthcare systems and by supporting green growth through optimized energy management and environmental monitoring.

Energy production is a fundamental input for economic activity but can generate environmental externalities that affect public health. Fossil-fuel-based production increases greenhouse gas emissions and pollution, which in turn elevate healthcare demands and expenditure. In contrast, renewable energy and low-carbon technologies reduce environmental and health risks. Theoretical perspectives suggest that the type, efficiency, and sustainability of energy production directly shape health outcomes, public expenditure needs, and progress toward green growth, creating a nexus among energy, health, and economic sustainability.

Air quality is theoretically influenced by the complex interplay of technological innovation, economic activity, energy production, urbanization, and green-growth policies. Artificial intelligence contributes to improved air quality by enhancing pollution monitoring, enabling predictive forecasting, optimizing energy efficiency, and supporting environmental governance (Muradov et al. 2024). Green growth strategies further support cleaner air by promoting renewable energy adoption, low-carbon industrial transformation, and sustainable production practices. Conversely, rapid economic growth, fossil-fuel-based energy production, and unplanned urbanization can degrade air quality unless mitigated by stringent environmental regulations and sustainable planning.

Data and methods

Data and variable description

This study uses annual time-series data for China covering the period 1990–2023. The data are collected from internationally recognized databases, including the World Development Indicators (WDI) of the World Bank, the Organization for Economic Cooperation and Development (OECD), and the U.S. Energy Information Administration (EIA). The selected variables capture health expenditure, artificial intelligence-related innovation, green growth, economic performance, renewable energy production, urbanization, and environmental quality in China.

1. Health expenditure, denoted as HLE, is measured as health expenditure per capita based on annual percentage changes. The data are obtained from the World Development Indicators (WDI). This variable reflects annual changes in per-person health-related spending in China and captures the evolution of health financing over the study period.
2. Artificial intelligence, denoted as AI, is measured using data retrieved from the Organization for Economic Cooperation and Development (OECD). AI-related innovation is proxied by triadic patent families. A triadic patent family refers to a set of patents filed at three major patent offices, namely the European Patent Office, the Japan Patent Office, and the United States

Patent and Trademark Office, to protect the same invention. This indicator is used because triadic patents generally represent inventions with higher technological and commercial value and reduce the bias associated with patent applications filed in only one national patent office. In this study, AI-related triadic patent families are used to capture China's internationally significant artificial intelligence innovation activities (Rasheed et al. 2025).

3. Green growth, denoted as GGR, is measured through the concept of Green GDP using OECD-based data. Unlike conventional GDP, which mainly measures the monetary value of economic output, Green GDP adjusts economic performance by accounting for environmental degradation and ecological costs. This measure provides a broader assessment of economic progress by linking growth with environmental responsibility. In the context of China, GGR is used to capture whether economic expansion is achieved while considering environmental damage, resource depletion, pollution, carbon emissions, and ecological sustainability. Therefore, this variable represents a sustainability-oriented measure of growth rather than a purely output-based economic indicator.
4. Economic growth, denoted as GDP, is measured using gross domestic product in constant 2015 US dollars. The data are collected from the World Development Indicators (WDI) of the World Bank.
5. Renewable energy production, denoted as EPO, is measured in quadrillion British thermal units. The data are obtained from the U.S. Energy Information Administration (EIA), International Energy Statistics. This variable captures the scale of renewable energy production in China and is included to assess the contribution of cleaner energy supply to green growth, environmental quality, and sustainable development.
6. Urbanization, denoted as URB, is measured as the percentage of the total population living in urban areas. The data are collected from the World Development Indicators (WDI). Urbanization is included because China's rapid urban expansion may influence health expenditure, energy demand, technological development, environmental quality, and long-term economic growth.
7. Air quality, denoted as AQR, is measured by PM2.5 air pollution, mean annual exposure, expressed in micrograms per cubic meter. The data are obtained from the World Development Indicators (WDI). PM2.5 exposure is used as an indicator of environmental quality and public health risk. Higher values indicate poorer air quality and greater exposure to fine particulate matter, which may affect health expenditure, population well-being, and sustainable economic development. The Fig. 2 are showing the data description.

Baseline model specification

Following recent theoretical and empirical studies, we specify the baseline econometric model as follows in Eq. (1):

$$HLE = f(AI, GRG, GDP, EPO, URB, ARQ) \tag{1}$$

In Eq. 1, Health expenditure (HLE) is modeled as a function of several key determinants, including artificial intelligence (AI), green growth (GRG), economic growth (GDP), energy production (EPO), urbanization (URB), and air quality (ARQ). In this framework, HLE reflects the level of resources allocated to healthcare, while AI represents the extent to which advanced digital technologies are integrated into health systems and related sectors. Green growth captures environmentally sustainable economic activities that may influence public health outcomes, and GDP accounts for overall economic performance. Energy production considers the scale and type of energy generation, which can have direct and indirect health impacts. Urbanization reflects demographic and infrastructural shifts that affect healthcare demand and delivery. Lastly, air quality measures environmental pollution, a critical factor influencing population health. Collectively, this model specifies how these factors interact to determine health expenditure. Equation (1) can be improved in the following way;

$$\begin{aligned} LnHLE_t = \varphi_0 + \varphi_1 LnAI_t + \varphi_2 LnGRG_t + \varphi_3 LnGDP_t \\ + \varphi_4 LnEPO_t + \varphi_5 LnURB_t + \varphi_6 LnARQ + \varepsilon_t \end{aligned} \tag{2}$$

In Eq. (2), the natural logarithm of health expenditure (LnHLE) is specified as a linear function of the natural logarithms of several explanatory variables, with φ_0 representing the intercept, φ_1 to φ_6 denote the regression coefficients associated with the predictor and control variables included in the model, and ε_t capturing unobserved influences or stochastic disturbances. Specifically, $(\varphi_1 = \frac{\Delta LnAI_t}{\Delta LnHLE_t} > 0)$ denotes the level of artificial intelligence adoption, which is expected to enhance healthcare efficiency and innovation; we hypothesize a positive relationship between AI and health expenditure, reflecting investments in technology-driven health services. $(\varphi_2 = \frac{\Delta LnGRG_t}{\Delta LnHLE_t} > 0)$ represents Green Growth, capturing sustainable development policies; countries with stronger commitment to green growth are likely to improve public health outcomes and promote long-term health system resilience, suggesting a positive effect on HLE. $(\varphi_3 = \frac{\Delta LnGDP_t}{\Delta LnHLE_t} > 0)$ accounts for overall economic

Fig. 2 Indicated data description

growth, as higher economic resources typically enable greater healthcare spending, which is expected to positively influence HLE. $(\varphi_4 = \frac{\Delta LnEPO_t}{\Delta LnHLE_t} > 0)$ measures energy production, which can indirectly affect health through environmental quality and access to reliable energy in healthcare infrastructure; higher energy availability may support better health service delivery. $(\varphi_5 = \frac{\Delta LnURB_t}{\Delta LnHLE_t} > 0)$ represents urbanization, reflecting population concentration and infrastructure development; its impact on HLE may be ambiguous, as urbanization can improve healthcare access but also increase environmental and lifestyle-related health risks. Finally, $(\varphi_6 = \frac{\Delta LnARQ_t}{\Delta LnHLE_t} > 0)$ captures air quality, a critical determinant of population health; poorer air quality is expected to increase healthcare demands, leading to higher health expenditure. Collectively, this specification allows the investigation of the relative contribution of technological, economic, environmental, and demographic factors to health expenditure, while controlling for unobserved shocks through the error term.

Econometric modeling approach

This section outlines the quantitative modeling framework used to investigate the empirical relationship between the HLE and AI, GRG, GDP, EPO, URB, and ARQ from 1990 to 2023. Considering the time-series structure of the dataset, a series of preliminary diagnostic tests were conducted to ensure that the variables satisfy the assumptions required for robust estimation. Initially, a unit root analysis was performed to establish the integration order of each series. Stationarity was further evaluated using the quantile-augmented Dickey–Fuller (ADF) test, a contemporary method that allows for a more nuanced assessment of time-series stability across different distributional quantiles. To examine the presence of non-linear dynamics, the Broock-Dechert-Scheinkman (BDS) test (Broock et al. 1996) was employed. Detecting non-linearity is essential, as it guides the selection of an appropriate modeling strategy; ignoring such patterns may result in biased or inconsistent parameter estimates. When non-linear behavior is identified, asymmetric modeling techniques are applied to capture these complexities effectively. The complete analytical framework is summarized in Fig. 2, providing a clear visualization of the stepwise approach adopted in this study.

Multivariate quantile-on-quantile regression (MQQR)

The MQQR approach proposed by Sim and Zhou (2015) is particularly suitable for uncovering nonlinear and distribution-dependent relationships among economic, environmental, and health-related variables. In the present study, it is applied to investigate how different quantiles of artificial intelligence (AI), green growth (GRG), gross domestic product (GDP), energy production (EPO), urbanization (URB), and air quality (ARQ) are associated with different quantiles of health expenditure in China (HLE). By moving beyond mean-based estimation, this method enables the identification of heterogeneous effects across the full distribution of both dependent and explanatory variables. Consequently, it provides deeper insight into whether the influence of AI, GGR, GDP, EPO, URB, and ARQ on HLE differs under low-, median-, and high-intensity conditions, thereby capturing potential asymmetries that conventional regression techniques may obscure.

Why MQQR? key methodological advantages The use of the MQQR approach is appropriate because it provides a richer and more flexible framework than conventional econometric techniques such as ordinary least squares (OLS) and standard quantile regression (QR). While OLS mainly captures average effects, it may conceal important variations that occur across lower, middle, and upper segments of the data distribution. Standard QR improves on this limitation by examining heterogeneity across different quantiles of the dependent variable; however, it does not fully capture how the relationship changes when both the dependent and explanatory variables vary across their own distributions. In contrast, MQQR allows the study to explore the full distributional dependence between health expenditure and its determinants, including artificial intelligence, green growth, GDP, energy policy uncertainty, urbanization, and air quality regulation.

I. A major strength of MQQR lies in its ability to identify asymmetric and nonlinear relationships. This is particularly important in economic, environmental, and health expenditure analysis, where the effects of explanatory variables may differ under low-, medium-, and high-intensity conditions. For example, the influence of AI or green growth on health expenditure may not be the same during periods of low technological development, moderate economic transition, or high environmental pressure. By estimating these heterogeneous effects across multiple quantile combinations, MQQR provides a more detailed understanding than mean-based regression models.

II. MQQR is also advantageous because of its robustness and flexibility. The method is less sensitive to outliers and is suitable for datasets characterized by non-normality, structural changes, and asymmetric patterns. These features make it especially useful for time-series and macroeconomic applications, where shocks, policy shifts, and uneven growth patterns are common. Moreover, by relying on local regression principles, MQQR gives greater weight to observations located near specific quantile points, thereby improving the precision of distribution-specific estimates.

III. Methodologically, MQQR bridges the strengths of quantile regression and non-parametric estimation. It helps overcome some limitations of traditional QR by capturing deeper forms of heterogeneity in variable relationships. At the same time, it reduces the dimensionality challenges often associated with fully non-parametric methods by applying a localized estimation strategy. As a result, MQQR offers a powerful empirical tool for examining whether the effects of AI, GGR, GDP, EPO, URB, and AQR on health expenditure in China vary across different economic, technological, and environmental conditions.

The MQQR framework specifies health expenditure in China (HLE) within a quantile-based distributional setting, where the conditional quantile of HLE is modeled as a function of the selected explanatory variables, namely artificial intelligence (AI), green growth rate (GGR), gross domestic product (GDP), energy policy uncertainty (EPO), urbanization (URB), and air quality regulation (AQR), Eq. (3) formalizes the relationship as follows:

$$Q_{HLE}(\tau \mid X_t) = f_\tau(X_{1t}^{\theta 1}, X_{2t}^{\theta 2}, X_{3t}^{\theta 3}, X_{4t}^{\theta 4}, X_{5t}^{\theta 5}, X_{6t}^{\theta 6})$$

Modify Eq. (3) for investigated variables;

$$Q_{HLE}(\tau \mid X_t) = f_\tau(AI_{1t}^{\theta 1}, GRG_{2t}^{\theta 2}, GDP_{3t}^{\theta 3}, EPO_{4t}^{\theta 4}, URB_{5t}^{\theta 5}, ARG_{6t}^{\theta 6}) \tag{3}$$

where, linear MQQR X_j denoted explanatory variable, $X_j^{\theta j}$ shows the quantile value of X_j. The first-order local linear approximation is:

$$Q_{HLE}(\tau \mid X_t) = \beta o(\tau, \theta) + \sum_{j=1}^{6} \beta_j(\tau, \theta_j) \left(X_{jt} - X_j^{\theta j} \right) \tag{4}$$

Now refine the Eq. (4) with investigated variables;

$$\begin{aligned} Q_{HLE}(\tau \mid X_t) = \beta o(\tau, \theta) \\ +\beta_1(\tau, \theta_1)(AI_t - AI^{\theta 1}) + \beta_2(\tau, \theta_2) \\ (GRG_t - GRG^{\theta 2}) + \beta_3(\tau, \theta_3) \\ (GDP_t - GDP^{\theta 3}) + \beta_4(\tau, \theta_4) \\ (EPO_t - EPO^{\theta 4}) \\ \beta_5(\tau, \theta_5)(URB_t - URB^{\theta 5}) \\ +\beta_6(\tau, \theta_6)(AQR_t - AQR^{\theta 6}) \end{aligned} \tag{5}$$

Redefine Eq. (5) empirical model specification;

$$\begin{aligned} Q_{HLE}(\tau \mid X_t) = \beta o(\tau, \theta) + \beta_1(\tau, \theta_1) \\ (AI_t - AI^{\theta 1}) + \beta_2(\tau, \theta_2)(GRG_t - GRG^{\theta 2}) \\ +\beta_3(\tau, \theta_3)(GDP_t - GDP^{\theta 3}) + \beta_4(\tau, \theta_4) \\ (EPO_t - EPO^{\theta 4})\beta_5(\tau, \theta_5)(URB_t - URB^{\theta 5}) \\ +\beta_6(\tau, \theta_6)(AQR_t - AQR^{\theta 6}) + \varepsilon_t^{\tau,\theta} \end{aligned} \tag{6}$$

where; $\tau \in (0,1)$ shows quantile dependent variable, $\theta = (\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6)$ indicated quantiles of explanatory variables, If the same quantile level is imposed across all explanatory variables, then: $\theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = \theta_6 = \theta$).

Empirical results

Table 1 and Fig. 3 present the statistical characteristics and normality properties of the study variables. LnURB shows the highest mean (21.36) and median (21.53), with a maximum value of 32.01 and the largest standard deviation (6.34), indicating that urbanization has the greatest magnitude and variability across the sample. LnGRG also records a relatively high mean (11.48) and median (11.43), but its low standard deviation (0.38) suggests a stable distribution. LnHLE, LnAI, and LnGDP show moderate central values and dispersion, while LnEPO and LnA have lower means of 1.81 and 1.68, respectively, with LnA displaying the lowest variability (stdev: 0.05). The skewness results indicate that most variables are approximately symmetric or only mildly

Table 1 Descriptive statistics

	LnHLE	LnAI	LnGRG	LnGDP	LnEPO	LnURB	LnARQ
Mean	4.145	2.640	11.481	3.589	1.813	21.360	1.678
Median	4.248	2.795	11.430	3.513	1.855	21.532	1.690
Maximum	5.943	3.867	12.200	4.530	2.103	32.010	1.766
Minimum	2.744	1.088	10.923	2.862	1.491	10.773	1.541
Std. Dev	0.931	0.962	0.383	0.519	0.221	6.335	0.050
Skewness	0.042	-0.318	0.454	0.659	-0.150	-0.067	-1.428
Kurtosis	2.081	1.662	1.937	2.401	1.373	1.861	4.636
Jarque–Bera	1.205	3.109	2.771	2.968	3.877	1.861	15.352

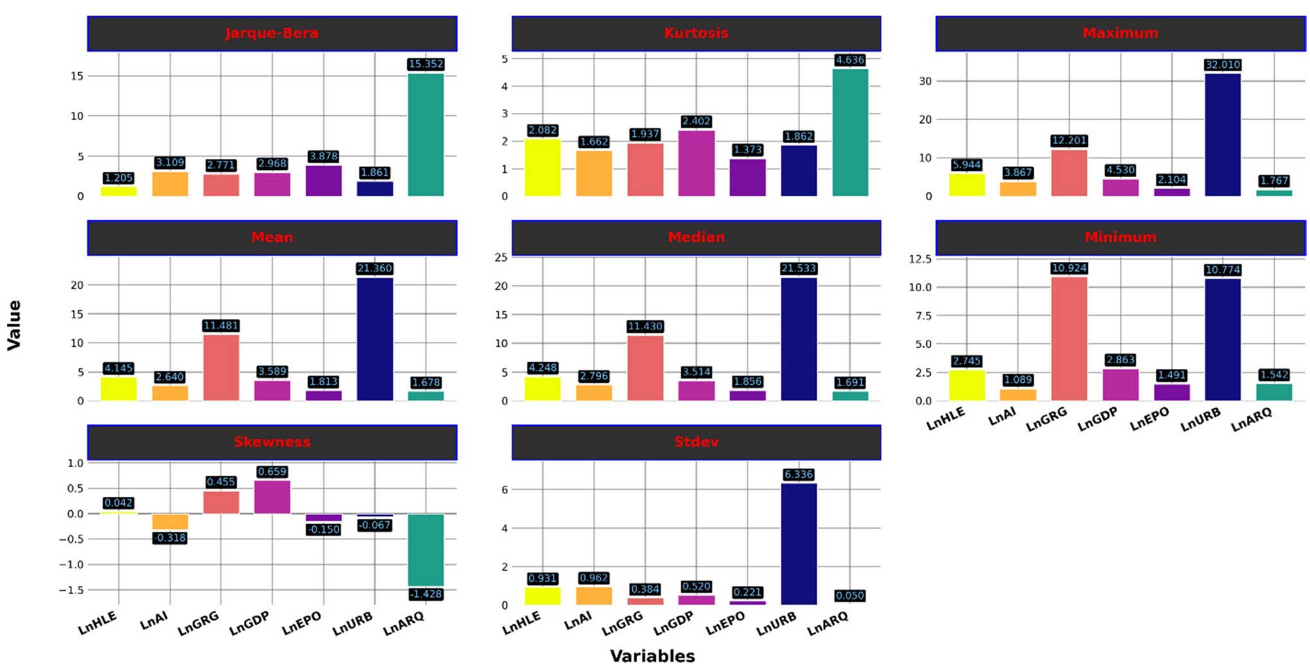


Fig. 3 Shows descriptive statistics

skewed, particularly LnHLE (0.04) and LnURB (−0.07), whereas LnGRG (0.45) and LnGDP (0.66) are moderately positively skewed, and LnAI (−0.32) and LnEPO (−0.15) are mildly negatively skewed. However, LnA shows strong negative skewness (−1.43), suggesting a longer left tail. Kurtosis values are below the normal benchmark of 3 for most variables, indicating relatively flat distributions, except for LnA, which has a kurtosis value of 4.64, reflecting a more peaked and heavy-tailed distribution. The Jarque–Bera statistics confirm that normality cannot be rejected for LnHLE, LnAI, LnGRG, LnGDP, LnEPO, and LnURB, as their values are below the conventional 5% critical threshold; however, LnA departs from normality with a Jarque–Bera value of 15.35. Overall, the variables exhibit acceptable distributional properties for further econometric analysis, although the non-normal behavior of LnA should be considered in subsequent diagnostic and robustness testing.

The correlation matrix in Fig. 4 shows the relationships among the study variables. LnHLE is strongly and positively correlated with LnURB (0.95), LnAI (0.93), LnGRG (0.92), LnGDP (0.91), and LnEPO (0.87), suggesting that these variables tend to increase together. In contrast, LnHLE has a moderate negative correlation with LnARQ (−0.51), indicating that higher LnARQ is associated with lower LnHLE. The matrix also shows strong positive correlations among several explanatory variables, especially LnAI and LnURB (0.99), LnAI and LnEPO (0.98), LnGRG and LnGDP (0.97), and LnEPO and LnURB (0.97). Meanwhile, LnARQ is negatively correlated with most variables, particularly LnGDP (−0.71) and LnGRG (−0.63). These results indicate clear interdependence among the variables and suggest that multicollinearity should be checked before conducting further regression analysis.

Table. 2 presents the results of the BDS (Brock et al. 1996) test for the variables LnHLE, LnAI, LnGRG, LnGDP, LnEPO, LnURB, and LnARQ across embedding dimensions M2 to M6. The resultsvsuggesting strong evidence of nonlinearity and potential chaotic dynamics within these time series. Notably, LnARQ shows extreme significance at M5 (0.8782) but drops sharply at M6 (0.1158), implying that its nonlinear dependence is highly sensitive to embedding dimension. Similarly, LnGDP and LnHLE show relatively lower BDS values in higher dimensions, indicating that their nonlinear structure is weaker compared with variables like LnAI and LnURB, which maintain high significance across dimensions. These findings suggest that linear modeling approaches may be insufficient to capture the complex dynamics of these sequences, justifying the application of

Fig. 4 Shows correlation graph

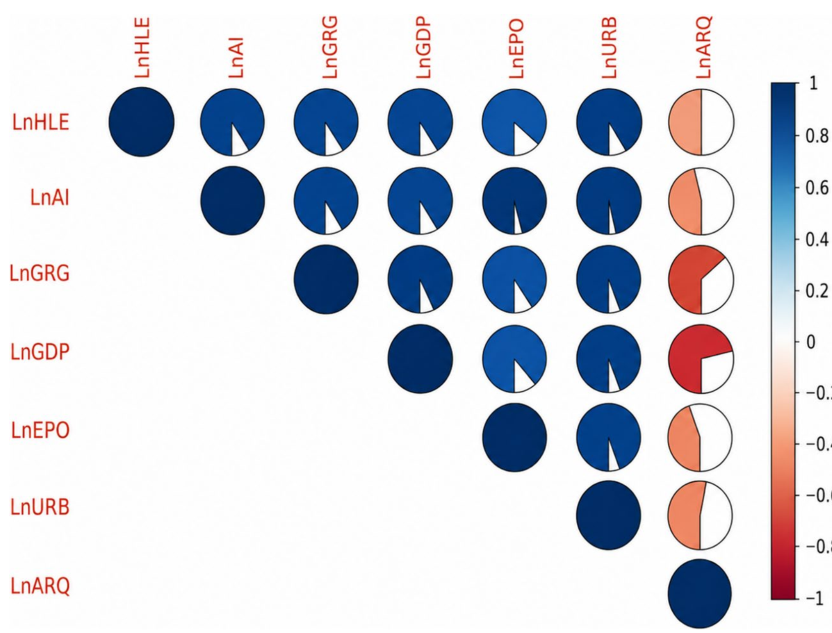


Table 2 BDS findings

	LnHLE	LnAI	LnGRG	LnGDP	LnEPO	LnURB	LnARQ
Dimension-2	0.1297	0.1998	0.1735	0.1671	0.1956	0.1985	0.1859
Dimension-3	0.2031	0.3411	0.2757	0.2579	0.3260	0.3330	0.3542
Dimension-4	0.2762	0.4391	0.3337	0.2959	0.4112	0.4253	0.1121
Dimension-5	0.3203	0.5080	0.3613	0.2914	0.4680	0.4943	0.8782
Dimension-6	0.3524	0.5603	0.3715	0.2353	0.5038	0.5454	0.1158

***$P<0.01$

nonlinear methods in subsequent analyses. The results indicate that most variables exhibit statistically significant BDS statistics at the 1% level (***P<0.01).

The Quantile–Quantile (QQ) plots in Fig. 5 compare the distributions of six log-transformed variables (LnAI, LnGRG, LnGDP, LnEPO, LnURB, LnHLE, LnARQ) against a theoretical normal distribution. LnAI, LnURB, and LnHLE points mostly align with the reference line, indicating these variables approximately follow a normal distribution, with minor deviations at the tails. LnGRG, LnGDP, LnEPO, and LnARQ show clear deviations at the tails and curvature, suggesting the presence of heavy tails or outliers. Overall, some variables satisfy the normality assumption, while others may require transformations or the use of robust/non-parametric statistical methods to ensure appropriate downstream analysis.

The results in the Fig. 6, indicate that, across most quantiles, the QADF test statistics for all variables remain below the critical values at the 1%, 5%, and 10% significance levels, suggesting that all series exhibit stationarity in their conditional distributions. Variables such as LnAI and LnGRG show stronger evidence of stationarity at lower quantiles (below 0.3–0.4), whereas variables like LnGDP, LnEPO, and LnURB display more consistent stationarity across the entire quantile range. These findings support the applicability of the quantile-based approach, as it confirms that there are no unit roots in either the central tendency or the tails of the distributions. This enhances the empirical robustness of subsequent quantile-on-quantile analyses.

The Fig. 7 presents the quantile KPSS test statistics for all variables across the full range of quantiles. Across all variables, the KPSS test statistics remain below the critical

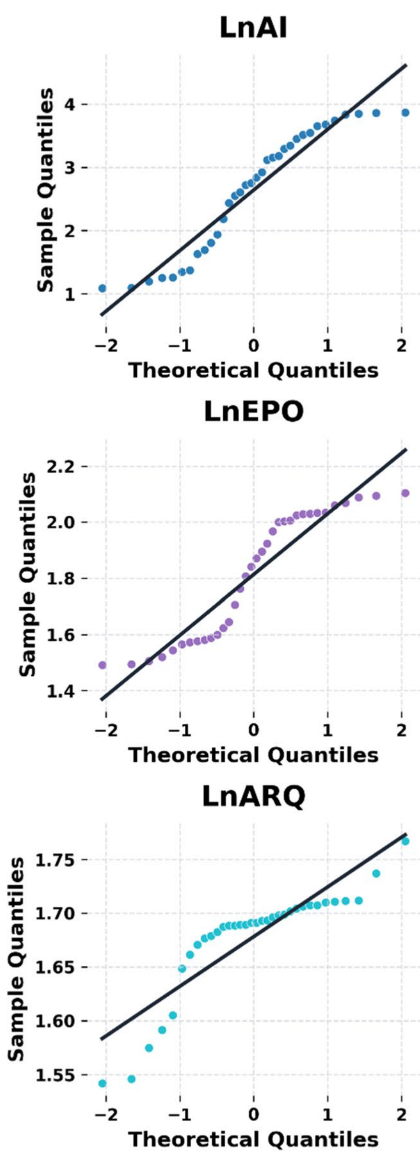


Fig. 5 Illustrated QQ plot

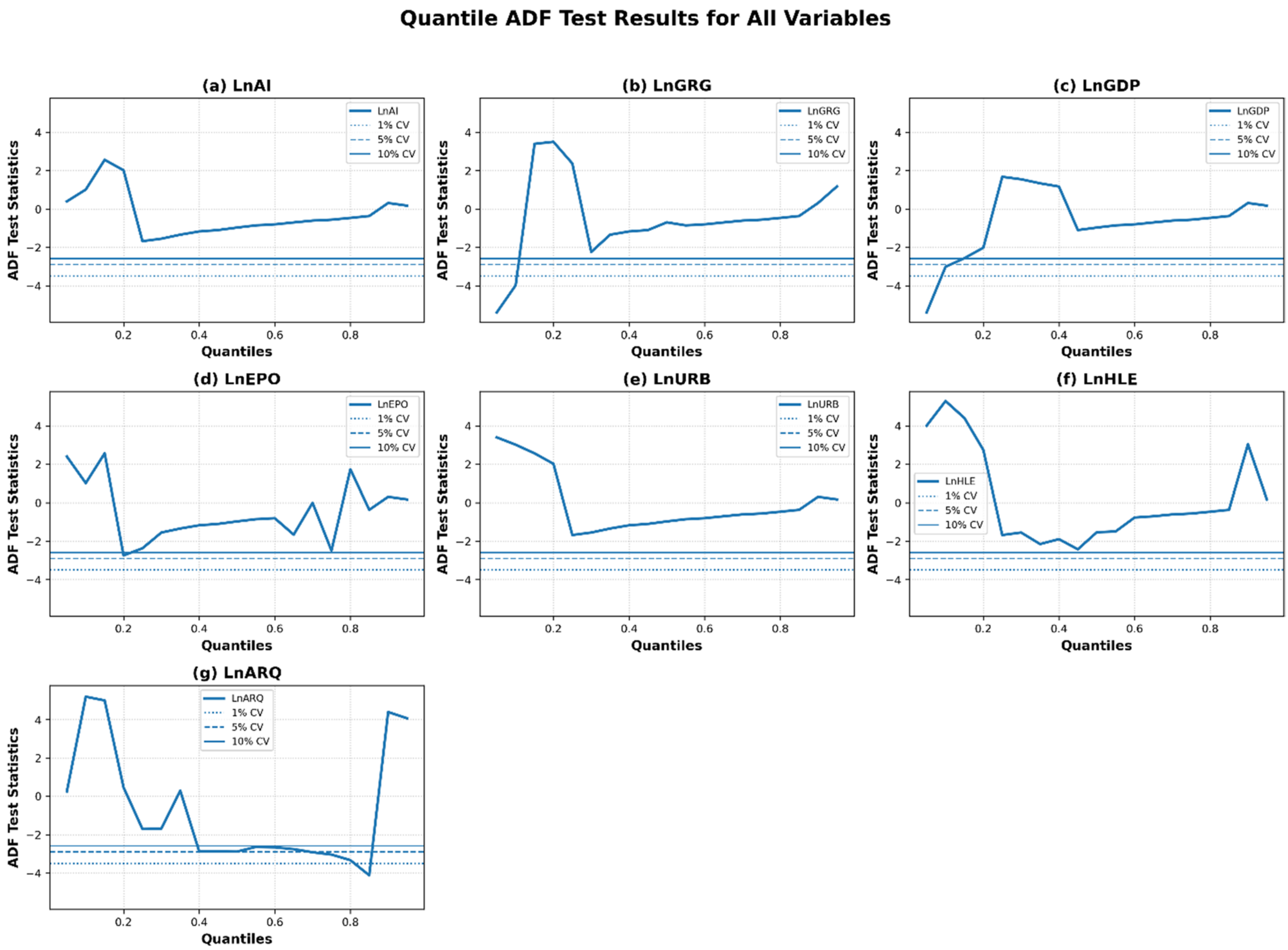


Fig. 6 Indicated QADF findings

values at the 1%, 5%, and 10% significance levels throughout most of the distribution, indicating that the null hypothesis of stationarity cannot be rejected. This confirms that the variables exhibit stationarity across their conditional distributions.

Some variables, such as LnGRG and LnHLE, show slightly higher KPSS values around the mid-quantiles (0.3–0.6), suggesting modest deviations from stationarity in these regions, but still below the critical thresholds, reinforcing the overall stationary behavior. Conversely, variables like LnAI, LnGDP, and LnEPO display consistent low KPSS values across nearly all quantiles, indicating strong evidence of stationarity across the entire distribution.

Main results derived from the multivariate QQR approach

The results of the multivariate quantile-on-quantile regression (QQR) and the conventional single-variable quantile regression (QR) are presented in the Fig. 8(a, b, c, d, e, f) for China, where LnHLE represents health expenditure, LnAI represents artificial intelligence, LnGDP represents economic growth, LnEPO represents energy production, LnURB represents urbanization, and LnARQ represents air quality. The main purpose of comparing the multivariate QQR results with the traditional QR estimates is to reveal the limitations of the conventional QR approach in capturing asymmetric and distribution-dependent relationships between health expenditure and its determinants. The traditional QR model is essentially a single-variable framework; therefore, it may ignore the influence of other key covariates that can substantially affect health expenditure. Although both QR and QQR are able to identify asymmetric associations across different quantiles, the multivariate QQR approach is more robust because it simultaneously incorporates the effects of other relevant variables, and these controls may alter not only the magnitude but also the direction of the estimated relationship. For example, in the case of LnAI, the QR and QQR results may appear similar in some tail regions, but the multivariate surface shows that

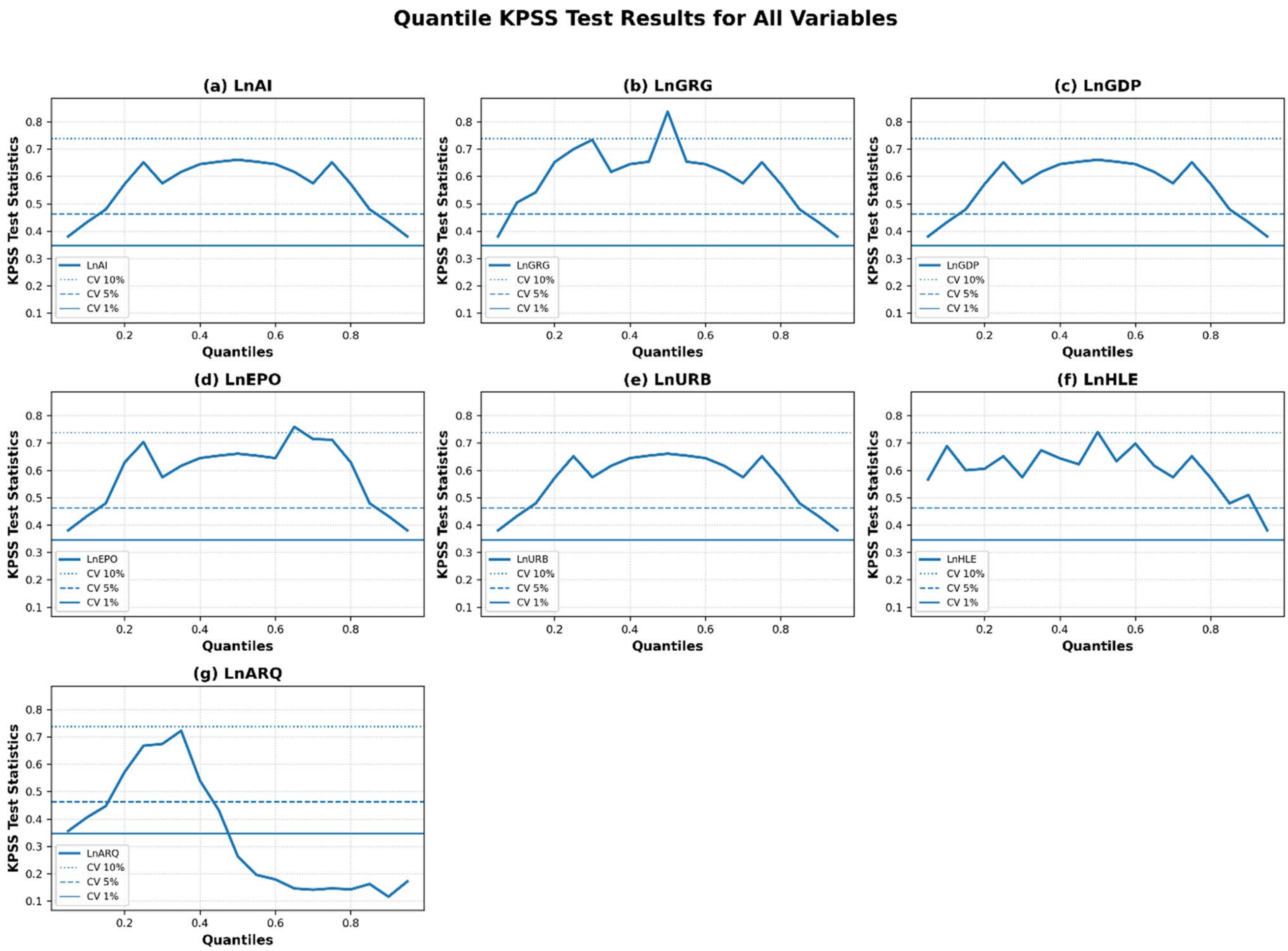
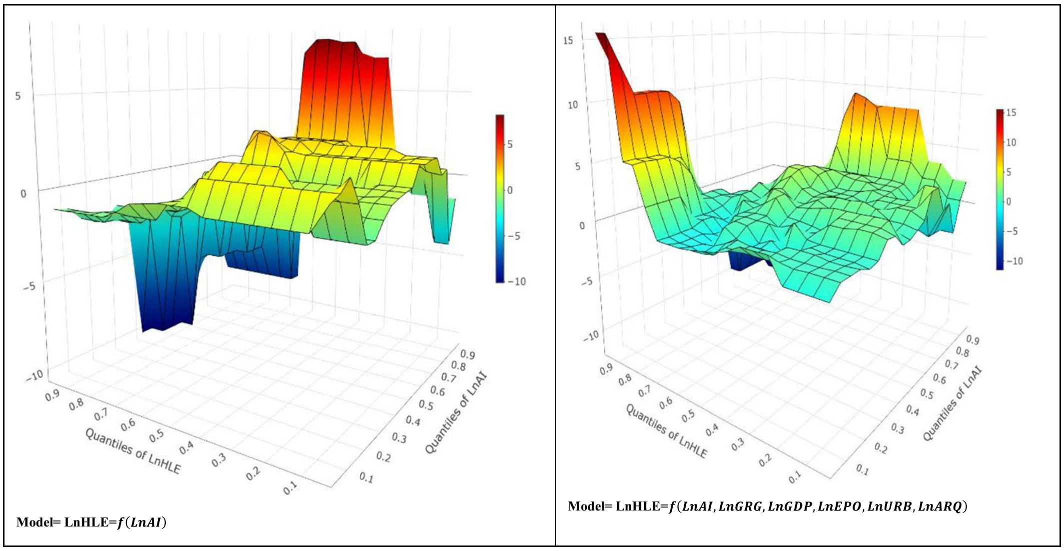


Fig. 7 Illustrated QKPSS results

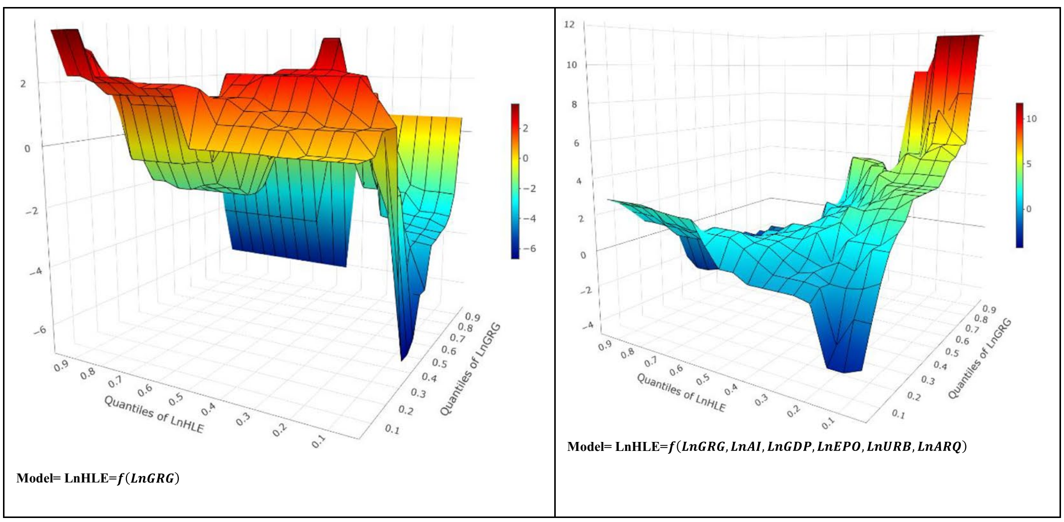
the relationship between artificial intelligence and health expenditure changes after controlling for economic growth, energy production, urbanization, air quality, and other selected determinants. Similar differences are also observed for LnGDP, LnEPO, LnURB, and LnARQ, suggesting that the effects of these variables on health expenditure are not uniform across the distribution but vary across lower, middle, and upper quantiles. Therefore, the QQR results provide a more comprehensive understanding of how artificial intelligence, economic growth, energy production, urbanization, and air quality affect health expenditure in China under different distributional conditions.

Robustness check

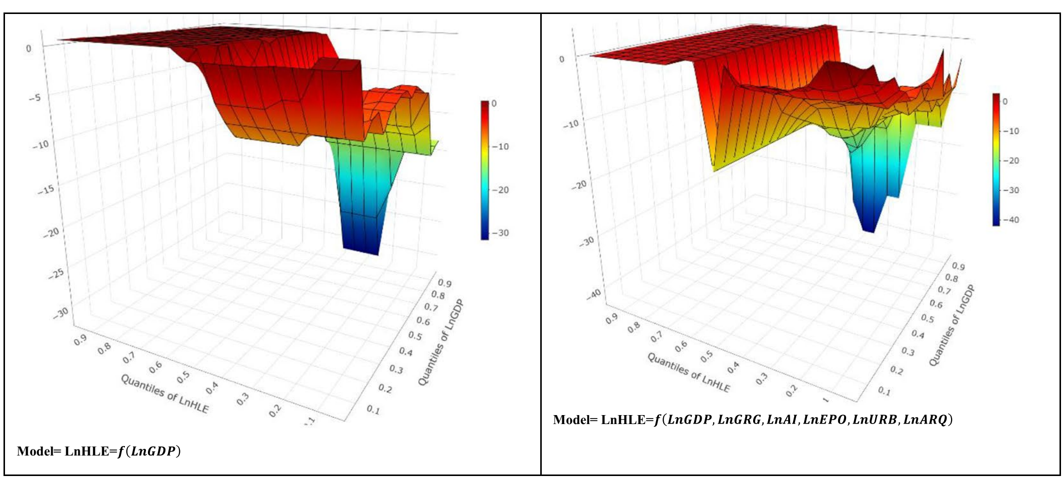
To verify the reliability of the QQR/M-QQR results, compares the conventional QR coefficients with the averaged QQR coefficients for the effects of LnAI, LnGRG, LnGDP, LnEPO, LnURB, and LnARQ on LnHLE across different quantiles. In general, both approaches produce broadly consistent patterns, particularly for LnAI, LnGDP, LnEPO, and LnURB, whose effects remain largely positive throughout the distribution. This consistency suggests that the QQR/M-QQR results are robust and can be reproduced using the standard QR framework. At the same time, some differences in coefficient size and trend are observed, especially for LnGRG and LnARQ. These differences are meaningful because they show that the QQR/M-QQR method captures deeper distributional heterogeneity that may not be fully visible in the ordinary QR estimates. In particular, LnARQ shows a more complicated pattern, with QR indicating a generally negative effect, while QQR suggests that the effect may shift from negative at lower quantiles to positive at higher quantiles. Therefore, the comparison confirms the overall reliability of the main findings while also highlighting the strength of the QQR/M-QQR approach in revealing quantile-specific and asymmetric relationships (Fig. 9).



(a) QR and QQR results of LnAI



(b) QR and QQR results of LnGRG



(c) QR and QQR results of LnGDP

Fig. 8 (**a**) QR and QQR results of LnAI. (**b**) QR and QQR results of LnGRG. (**c**) QR and QQR results of LnGDP. (**d**) QR and QQR results of LnEPO. (**e**) QR and QQR results of LnURB. (**f**) QR and QQR results of LnARQ

Fig. 9 Shows the robustness of QR and QQR

Discussion

Figure 8a discusses the effect of artificial intelligence (LnAI) on health expenditure (LnHLE) in China. The QR and QQR results indicate that the relationship between AI and health expenditure is not linear or uniform across quantiles. In the traditional QR surface, the effect of AI appears mixed, with negative effects in some lower and middle quantile regions and positive effects in selected higher quantile regions. However, the multivariate QQR result provides a more complete picture by showing that the AI–health expenditure nexus changes after controlling for economic growth, energy production, urbanization, air quality, and other covariates. The positive regions suggest that higher AI development may be associated with increased health expenditure, especially when AI adoption requires large-scale investment in digital infrastructure, intelligent diagnostic systems, hospital information platforms, and medical technology upgrading. In China, this is practically plausible because AI-driven healthcare transformation often involves high initial costs, including equipment procurement, data-system integration, clinician training, and regulatory adaptation. Conversely, the negative regions suggest that AI may also reduce health expenditure pressure in some quantile combinations by improving diagnostic accuracy, reducing unnecessary procedures, enhancing hospital efficiency, supporting early disease detection, and optimizing resource allocation. Therefore, the implication is that AI should not be treated merely as a cost-increasing technology; rather, its fiscal effect depends on the stage of adoption and the maturity of the healthcare system. For policy practice, China should promote AI applications that reduce inefficiency and duplication in health services while avoiding uncontrolled technology-driven expenditure expansion.

Figure 8b presents the QR and QQR results for LnGRG and health expenditure. The surfaces show that the effect of LnGRG on health expenditure is heterogeneous across quantiles, rather than consistently positive or negative. The QR result indicates that the association changes across the distribution of health expenditure, while the QQR surface shows a more complex pattern after the inclusion of other determinants. Positive effects in some upper quantile regions imply that improvements in GRG-related development may be accompanied by higher health expenditure, possibly because structural transformation, environmental upgrading, and green investment require additional public spending, institutional adjustment, and health-system support. In the Chinese context, green transition policies may initially increase fiscal commitments through pollution-control programs, occupational health protection, environmental monitoring, and public-health compensation in industrial regions. However, the negative regions suggest that GRG may reduce health expenditure in other quantile combinations by lowering environmental exposure, improving ecological conditions, and reducing pollution-related disease burdens. This indicates that GRG has both transition-cost and long-term health-saving effects. The practical implication is that green development strategies should be coordinated with health policy: environmental upgrading should be accompanied by preventive healthcare, pollution-risk surveillance, and targeted support for regions where green transition may temporarily raise health-related fiscal pressure.

Figure 8c shows the relationship between economic growth (LnGDP) and health expenditure. Compared with other variables, the GDP surfaces display a more pronounced negative pattern across many quantile combinations, particularly in the QQR model. This suggests that economic growth does not automatically translate into higher health expenditure across all distributional conditions. One possible explanation is that stronger economic performance may improve infrastructure, employment, household income, sanitation, nutrition, and access to preventive services, thereby reducing some categories of avoidable health expenditure. In addition, economic development may improve healthcare efficiency through better hospital capacity, insurance coverage, and public-health investment. However, the sharp negative regions also indicate that the GDP–health expenditure relationship is highly conditional. In China, economic growth may reduce health expenditure pressure when it is associated with improved public infrastructure and preventive capacity, but it may increase health burdens if growth is accompanied by pollution, urban stress, population aging, and lifestyle-related disease. Therefore, the practical implication is that economic growth alone is insufficient as a health-policy strategy. China should ensure that growth is health-oriented, environmentally sustainable, and supported by equitable healthcare financing, otherwise the benefits of GDP growth may not translate into lower long-term health expenditure.

Figure 8d illustrates the effect of energy production (LnEPO) on health expenditure. The QR result shows that energy production has a predominantly negative effect across several quantile areas, with positive effects appearing mainly in selected higher quantile regions. The QQR result confirms that the relationship is asymmetric and strongly dependent on the joint distribution of energy production and health expenditure. The negative effect may suggest that adequate energy production supports healthcare delivery, industrial productivity, household welfare, and medical-service accessibility, thereby reducing certain expenditure pressures. Reliable energy supply is essential for hospital operation, cold-chain systems, diagnostic equipment, digital health infrastructure, and emergency services. However, the positive regions indicate that higher energy production may also increase health expenditure when energy expansion is associated with environmental degradation, fossil-fuel dependence, air pollution, and occupational health risks. This interpretation is particularly relevant for China, where energy security and environmental health remain closely linked. The policy implication is that expanding energy production should be accompanied by cleaner energy structures, stricter emission controls, and health-impact assessments. The objective should not be merely to increase energy output, but to decouple energy production from pollution-related health expenditure.

Figure 8e reports the effect of urbanization (LnURB) on health expenditure. The QR surface suggests an unstable and nonlinear relationship, while the QQR model reveals stronger quantile-specific heterogeneity after controlling for other variables. Positive regions indicate that urbanization may increase health expenditure by expanding healthcare access, increasing hospital utilization, improving insurance coverage, and raising public demand for higher-quality medical services. In China, rapid urbanization often brings more people into formal healthcare systems, which may increase recorded health expenditure even when health outcomes improve. At the same time, urbanization can generate additional health risks through air pollution, traffic congestion, psychological stress, sedentary lifestyles, and unequal access to urban public services. The negative regions, however, suggest that urbanization may reduce health expenditure in some quantiles by improving infrastructure, sanitation, healthcare accessibility, emergency response, and economies of scale in public-service delivery. Therefore, the results imply that urbanization has a dual effect: it can either increase health expenditure through higher service demand and urban health risks, or reduce expenditure pressure through improved infrastructure and healthcare efficiency. For practical policy, China should promote health-oriented urbanization by integrating urban planning with pollution control, primary healthcare expansion, elderly care, public transport, green space development, and disease-prevention programs.

Figure 8f presents the relationship between air quality (LnARQ) and health expenditure. The QR and QQR surfaces show that the effect of air quality on health expenditure is clearly asymmetric across quantiles. The positive areas suggest that changes in air quality may be associated with higher health expenditure in certain distributional conditions, especially where improved environmental governance occurs together with higher public-health investment, stronger monitoring capacity, and greater healthcare utilization. In developed regions of China, better air quality may coincide with higher health spending because richer provinces often invest more simultaneously in environmental protection and healthcare services. However, the negative regions indicate that improved air quality may reduce health expenditure pressure by lowering the incidence of respiratory disease, cardiovascular disease, pollution-related hospitalization, and long-term morbidity. This is consistent with the practical expectation that cleaner air reduces preventable disease burdens. The implication is that air-quality improvement should be regarded not only as an environmental objective but also as a health-financing strategy. In China, sustained reductions in air pollution could help contain long-term healthcare costs, particularly in regions with high baseline pollution exposure and high health expenditure pressures. However, the interpretation of LnARQ should be clearly defined in the manuscript: if a higher value of ARQ represents poorer air quality or pollution intensity, the direction of interpretation should be reversed accordingly.

Conclusion and policy implications

This study examined the nonlinear and distribution-dependent determinants of health expenditure in China by analyzing the effects of artificial intelligence, economic growth, energy production, urbanization, and air quality on health expenditure. Using annual time-series data for China and applying a multivariate quantile-on-quantile regression framework, the study provides evidence that the relationship between health expenditure and its key technological, economic, energy, demographic, and environmental determinants is heterogeneous across quantiles. The findings confirm that conventional mean-based models are insufficient to capture the complex dynamics of health expenditure, because the effects of AI, GDP, EPO, URB, and ARQ vary substantially across lower, middle, and upper segments of the health expenditure distribution.

The empirical results show that artificial intelligence has a mixed and quantile-specific effect on health expenditure. In some quantile regions, AI is associated with higher health expenditure, reflecting the substantial investment required for digital health infrastructure, intelligent diagnostic systems, hospital information platforms, data governance, and workforce training. However, in other quantile regions, AI appears to reduce expenditure pressure by improving diagnostic accuracy, optimizing resource allocation, reducing unnecessary procedures, and strengthening preventive health management. This suggests that AI should not be viewed simply as a cost-increasing technology. Its long-term fiscal effect depends on whether China can move from technology adoption to efficient, integrated, and prevention-oriented digital health governance.

Energy production has an asymmetric effect on health expenditure. Adequate and reliable energy production can support hospital operations, diagnostic technologies, digital health systems, cold-chain logistics, emergency services, and broader welfare improvements, thereby reducing certain health expenditure pressures. Nevertheless, when energy expansion is linked to fossil-fuel dependence, industrial emissions, air pollution, and occupational health risks, it can increase healthcare costs. This finding highlights the need to decouple energy production from pollution-related health expenditure. China's energy policy should therefore prioritize cleaner energy structures, stricter emission control, renewable energy expansion, and systematic health-impact assessment of energy-sector development.

Urbanization also demonstrates a dual effect. On one hand, urbanization may increase health expenditure by expanding healthcare access, increasing hospital utilization, raising public demand for high-quality medical services, and exposing populations to urban health risks such as air pollution, congestion, psychological stress, sedentary lifestyles, and unequal access to public services. On the other hand, urbanization may reduce expenditure pressure when it improves sanitation, infrastructure, emergency response capacity, primary healthcare access, and economies of scale in public-service delivery. These findings suggest that China should pursue health-oriented urbanization by integrating urban planning with pollution control, public transport, green spaces, elderly care, primary healthcare expansion, and chronic disease prevention.

Air quality remains a critical determinant of health expenditure. The results indicate that its effect is asymmetric across quantiles. Improved air quality may reduce health expenditure by lowering the burden of respiratory disease, cardiovascular disease, pollution-related hospitalization, and long-term morbidity. However, in some regions, better air quality may coincide with higher public spending because wealthier provinces often invest simultaneously in environmental protection, healthcare services, and monitoring systems. Therefore, air-quality improvement should be understood not only as an environmental policy objective but also as a long-term health-financing strategy. Sustained reductions in pollution exposure can help China contain preventable healthcare costs, especially in regions with historically high pollution burdens.

Limitation and future direction

This study has several data-related limitations that should be acknowledged. First, the analysis relies on aggregate annual time-series data for China, which may conceal important provincial, urban–rural, and regional differences in health expenditure, artificial intelligence development, energy structure, urbanization, and air-quality exposure. Second, some variables are represented by proxy indicators; for example, AI is measured through AI-related triadic patent families, while air quality is captured mainly through PM2.5 exposure, which may not fully reflect the broader dimensions of digital health adoption, environmental pollution, or healthcare-system transformation. Third, the relatively limited annual sample size may restrict the ability to capture short-term policy shocks, structural breaks, and rapid technological changes, especially in a fast-evolving economy such as China. Although the MQQR approach is appropriate for identifying nonlinear and quantile-specific relationships among HLE, AI, GDP, EPO, URB, and ARQ, the method does not fully eliminate possible endogeneity, omitted-variable bias, or reverse causality among economic growth, health expenditure, environmental quality, and technological innovation. Future research should therefore extend the analysis using provincial- or city-level panel data, disease-specific health expenditure, separate indicators for public and private health spending, more direct measures of healthcare AI adoption, and broader environmental indicators such as SO_2, NO_2, O_3, CO_2 emissions, and renewable versus fossil-based energy production. Future studies may also apply spatial econometric models, causal identification strategies, threshold models, dynamic panel methods, and machine-learning-based forecasting approaches to better explain how technological progress, clean energy transition, urban development, and environmental governance jointly affect the sustainability of China's healthcare financing system.

Author' contributions

Syed Tauseef Hassan: Investigation, wrote original draft. Wang Long: Software and Visualization. Cheng Fei: Data Collection and Methodology. Kan Wu: validation and discussion. Shahid Ali: edit, review, and literature review.

Acknowledgements Declaration of generative AI and AI-assisted technologies in the manuscript preparation process. During the preparation of this work, the author utilized Generative AI (OpenAI, Grammarly) to enhance the clarity, coherence, and language quality of the manuscript. After using this tool, the author thoroughly reviewed, edited, and verified all content to ensure accuracy and originality, and takes full responsibility for the content of the published article.

Funding The publication of this paper was supported by the Research Start-up Fund for Doctoral Professors at Hezhou University, with grant number: 2023BSQD05.

Data availability The datasets used and/or analyzed during the current study are also available from the corresponding author on reasonable request.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare that they have no competing. interests.

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