

Examining the Quantile Effects of Income Inequality, Relative Deprivation, and Modern Technologies on Health Expenditures in Iran

Sima Safarzadeh¹, Lotfali Agheli^{2,*} and Khashayar Seyedshokri³



¹ Department of Health Economics, SR.C., Islamic Azad University, Tehran, Iran; 

² Department of Economics, Faculty of Economics, Tarbiat Modares University, Tehran, Iran; 

³ Department of Economics, CT.C., Islamic Azad University, Tehran, Iran; 

* Correspondence: aghelik@modares.ac.ir

Citation: Safarzadeh, S., Agheli, L., & Seyedshokri, K. (2027). Examining the Quantile Effects of Income Inequality, Relative Deprivation, and Modern Technologies on Health Expenditures in Iran. *Business, Marketing, and Finance Open*, 4(8), 1-20.

Received: 08 April 2026

Revised: 13 September 2026

Accepted: 20 September 2026

Initial Publication: 29 October 2026

Final Publication: 01 August 2027



Copyright: © 2027 by the authors. Published under the terms and conditions of Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) License.

Abstract: This study examines the quantile effects of income inequality, relative deprivation, and modern technologies on health expenditures in Iran during the period 1991–2024. In terms of its objective, the study is applied research, while in terms of its nature, it adopts a descriptive-analytical approach and falls within the category of ex post facto research. Quantile regression was employed to estimate the long-run relationships among the variables and analyze distributional effects, thereby allowing the effects of the explanatory variables to be examined across all quantiles of the health expenditure distribution. The dependent variable is government public expenditure on health, while the independent variables include income inequality, relative deprivation in human capital, human capital, the development of modern technologies (ICT), capital formation, employment, population, CO₂ emissions, and the COVID-19 crisis. The results of the stationarity and cointegration tests indicate that all variables become stationary after first differencing and that at least four long-run cointegrating relationships exist among the variables. The quantile regression findings demonstrate that income inequality and relative deprivation have positive and statistically significant effects on health expenditures, with these effects becoming stronger at higher quantiles. In contrast, modern technologies have a negative and statistically significant effect on health expenditures, such that a higher level of ICT development is associated with lower government health expenditures. Other control variables, including population, capital formation, employment, and CO₂ emissions, also exhibit heterogeneous effects on health expenditures. The findings indicate that income inequality and relative deprivation are important drivers of increased health expenditures, whereas the development of modern technologies can alleviate expenditure pressures by improving the efficiency of healthcare systems. These findings provide practical implications for economic and health policymakers, particularly in designing policies aimed at reducing inequality and enhancing productivity and efficiency in the health sector.

Keywords: Health Expenditures; Income Inequality; Relative Deprivation; Human Capital; Modern Technologies

1. Introduction

Health expenditure constitutes one of the most important components of public expenditure and has become a central concern in health economics, public finance, and development policy because of its direct relationship with population health, household welfare, labor productivity, and the sustainability of public budgets. In recent decades, the growth of healthcare costs has accelerated in many countries as a result of demographic change, epidemiological transition, technological development, environmental pressures, and increasing demand for

higher-quality medical services. The expansion of healthcare spending is not necessarily undesirable, since adequate expenditure can improve access to preventive and curative services and ultimately increase population health; nevertheless, persistent increases in expenditure may place considerable pressure on government budgets and household resources when they are not accompanied by corresponding improvements in efficiency and equity. Changes in national healthcare spending therefore have important implications for the fiscal sustainability of health systems and for governments' capacity to finance other social and economic priorities [1]. In developing economies, these challenges are often more pronounced because health systems operate under resource constraints while simultaneously confronting inequality, poverty, environmental deterioration, rapid urbanization, and unequal access to healthcare. Consequently, identifying the economic, social, technological, and environmental determinants of health expenditures has become essential for designing evidence-based health and economic policies.

The distribution of income represents one of the most important socioeconomic mechanisms through which health expenditures may be affected. Income inequality can influence health expenditure through multiple and potentially reinforcing channels. At the individual and household levels, unequal income distribution may restrict access to preventive healthcare, adequate nutrition, education, and favorable living conditions among lower-income groups. At the societal level, high inequality may produce unequal exposure to health risks and differences in access to healthcare resources, potentially increasing the burden of preventable diseases and the demand for publicly financed medical services. Evidence from Iran indicates that health inequality across provinces is associated with economic and social determinants and that disparities in economic opportunities and resources can translate into unequal health outcomes [2]. The interaction between healthcare expenditure and income distribution is also potentially bidirectional. Health expenditures may alter inequality by changing households' financial burden and access to services, while inequality itself may determine the level and composition of health expenditure [3]. Research on income distribution in Iranian urban areas has further demonstrated that the determinants of inequality can exhibit heterogeneous effects across different points of the income distribution, indicating the importance of analytical methods capable of capturing distributional heterogeneity rather than focusing exclusively on average effects [4]. More recent quantile-based evidence concerning Iranian urban households similarly indicates that the effects of income inequality and relative deprivation on health expenditure may differ across expenditure levels, emphasizing that distribution-sensitive relationships should be analyzed explicitly [5].

The relationship between socioeconomic inequality and health is not necessarily uniform across populations or across different levels of health and expenditure. Socioeconomic disparities can generate heterogeneous health consequences depending on the position of individuals or groups within the broader economic distribution. Evidence regarding the heterogeneous influence of socioeconomic inequality on population health suggests that aggregate average relationships may conceal substantial variation across socioeconomic groups and health conditions [6]. This issue is particularly important when health expenditure is considered, because households and governments facing relatively low health expenditures may respond differently to inequality than those located at the upper tail of the expenditure distribution. Furthermore, healthcare costs themselves can affect conventional measures of poverty and economic deprivation. Medical expenditures may substantially alter estimates of disposable resources and poverty status, especially among economically vulnerable households whose healthcare needs are relatively high [7]. Inequalities in out-of-pocket expenditure similarly remain a major challenge for universal health coverage because differences in household financial capacity may determine access to healthcare and exposure to catastrophic spending [8]. These considerations demonstrate that analyses based solely on mean

health expenditures may provide an incomplete representation of the relationship between inequality and the financial burden of healthcare.

A related concept with particular relevance to health expenditure is relative deprivation. Unlike absolute deprivation, which refers to insufficient access to basic economic resources, relative deprivation reflects individuals' or households' perceived or measurable disadvantage relative to relevant reference groups. Relative deprivation can arise from disparities in wages, education, human capital, employment opportunities, or broader socioeconomic position. From a health economics perspective, relative deprivation may influence healthcare expenditure through both direct and indirect pathways. Individuals with relatively disadvantaged economic or educational positions may experience greater psychological stress, reduced access to health information, weaker preventive behavior, less favorable working conditions, and greater exposure to environmental and social health risks. These mechanisms can contribute to poorer health outcomes and increase subsequent demand for healthcare. Wage-related deprivation may constrain households' ability to invest in preventive health, whereas deprivation in human capital may limit health literacy and the effective utilization of medical services. The recent application of quantile analysis to income inequality and relative deprivation in Iran indicates that these factors can exert heterogeneous effects on health expenditures across different expenditure quantiles [5]. Such evidence strengthens the argument that relative deprivation should be analyzed independently rather than being subsumed entirely within conventional measures of income inequality.

Alongside socioeconomic inequality, rapid technological transformation is fundamentally changing the structure, organization, and financing of healthcare systems. Emerging technologies encompass a broad range of innovations, including information and communication technology, artificial intelligence, telemedicine, digital health platforms, electronic health records, automated clinical decision-support systems, advanced diagnostic technologies, flexible electronics, and data-driven management tools. These technologies have the potential to improve the quality, accessibility, timeliness, and efficiency of healthcare services. In Iran, emerging technologies have been identified as important instruments for improving healthcare delivery by facilitating more efficient service provision and strengthening the technological capacity of health organizations [9]. Research on technology selection in healthcare supply chains also shows that the adoption of emerging technologies depends on multiple organizational, technical, and operational factors, indicating that technological development must be incorporated into broader health-system planning [10]. Emerging technologies are additionally being applied across medical and biological sciences, expanding the technological infrastructure available for diagnostics, treatment, monitoring, and research [11]. Their role has also become increasingly important in hospital and healthcare crisis management, where digital systems can improve coordination, responsiveness, and the allocation of limited resources during emergencies [12].

Information and communication technology may influence health expenditures in opposing directions. In the short term, technological adoption may require substantial investment in hardware, software, infrastructure, employee training, cybersecurity, and system integration. Hospitals and other healthcare organizations therefore increasingly need reliable methods for measuring and comparing their information technology expenditures across institutions [13]. In the longer term, however, digitalization may reduce expenditure by improving administrative efficiency, lowering transaction costs, preventing duplicated diagnostic procedures, facilitating remote care, supporting preventive interventions, and enabling more effective allocation of medical resources. Evidence from municipalities indicates that information technology and the effectiveness of public management are associated with health expenditures, illustrating the close connection between digital infrastructure and healthcare resource

management [14]. Earlier evidence from developing countries also suggests that information and communication technology can influence health expenditures in conjunction with broader macroeconomic factors such as economic openness and energy transformation [15]. More recent research in Iran similarly indicates that emerging health technologies can alter patterns of household treatment expenditure, particularly when differences in access to technology are taken into consideration [16]. Consequently, technological development should not be treated merely as a cost-increasing input; it may also function as a productivity-enhancing mechanism capable of reducing unnecessary expenditure.

Technological innovation may additionally reduce healthcare costs through improved disease prevention, early detection, and targeted medical intervention. Biomarkers and technologies related to disease identification, for example, may generate economic savings when they facilitate earlier diagnosis and more efficient treatment pathways [17]. Artificial intelligence has considerable potential in primary medical services because of its high processing speed and ability to support clinical assessment, diagnosis, and decision-making [18]. Advances in sustainable technologies are also introducing new forms of flexible electronics into modern healthcare ecosystems, including monitoring and diagnostic technologies that may contribute to the transition toward more resource-efficient healthcare delivery [19]. At the same time, modern healthcare technologies extend beyond direct patient treatment to include sustainable management practices. Contemporary medical waste management increasingly relies on innovative technologies to reduce environmental burdens and improve operational sustainability within healthcare institutions [20]. These developments indicate that the relationship between technology and health expenditure involves not only clinical effectiveness but also environmental, organizational, and managerial efficiency.

Nevertheless, technological development does not automatically produce equitable or cost-saving outcomes. Digital health technologies can generate or reinforce inequalities when access to digital infrastructure, technological literacy, connectivity, devices, or high-quality digital services differs across socioeconomic groups [21]. Consequently, the benefits of health digitalization may be disproportionately captured by populations with higher income, education, and technological capabilities unless policies explicitly address the digital divide. This interaction between technology and inequality is especially relevant for health expenditure because unequal access may influence both the demand for healthcare and the efficiency with which health resources are used. Modern health-sector transformation therefore requires not only the adoption of technology but also institutional restructuring, leadership, and effective governance. Evidence from healthcare leaders shows that transformation toward modern healthcare models involves organizational redesign, integration of new service-delivery mechanisms, and improvements in health-system management [22]. Thus, technological progress should be examined in conjunction with socioeconomic inequality and institutional efficiency rather than as an isolated determinant.

The efficiency with which healthcare resources are transformed into services and health outcomes is another important dimension of expenditure analysis. Higher expenditure does not necessarily imply better performance if resources are allocated inefficiently. Evidence from Iran shows that technical efficiency and managerial capability are central to the performance of the health sector, indicating that improvements in management can enhance outcomes without proportionate increases in resource use [23]. International evidence similarly demonstrates the importance of performance measurement at the level of health centers, where effectiveness-based data envelopment analysis can identify substantial differences in organizational performance and resource utilization [24]. Accordingly, emerging technologies may affect health expenditure partly by enhancing managerial

capabilities, improving information flows, and increasing the efficiency of healthcare institutions. Health-sector financial conditions may also be affected by broader market dynamics. Evidence concerning price bubbles in healthcare-related firms in the Tehran Stock Exchange illustrates that health-sector economic activity is intertwined with financial-market behavior and may therefore be subject to financial as well as operational pressures [25].

Environmental conditions constitute another major determinant of healthcare needs and expenditures. Air pollution, carbon dioxide emissions, energy use, industrialization, and urbanization can affect population health by increasing exposure to respiratory, cardiovascular, and other environmentally related diseases. Research investigating healthcare costs in Bangladesh emphasizes the complex relationships among environmental quality, economic growth, energy consumption, industrialization, urbanization, forest area, and healthcare expenditure [26]. The role of environmental factors is particularly important in developing economies undergoing rapid urban and industrial transformation. Carbon emissions may raise healthcare expenditure by deteriorating environmental quality and increasing the prevalence of pollution-related illnesses. At the same time, the relationship between environmental quality, health expenditure, and quality of life may vary considerably across countries. Evidence from African economies indicates that carbon dioxide emissions and health expenditures can moderate the determinants of quality of life, further illustrating the interdependence of environmental and healthcare variables [27]. Modern technological development may contribute to addressing these environmental-health pressures when cleaner and more sustainable technologies are integrated into healthcare systems and broader economic infrastructure.

Health expenditure is therefore shaped by a multidimensional set of forces involving socioeconomic distribution, human capital, environmental conditions, labor-market characteristics, capital formation, population dynamics, technological change, and institutional performance. These forces may become particularly pronounced during major health shocks. The COVID-19 pandemic demonstrated that global health crises can rapidly alter the demand for healthcare, increase public expenditure, disrupt routine service provision, and accelerate the adoption of digital and remote technologies. The pandemic also exposed existing inequalities in access to health services and technological infrastructure and highlighted the importance of resilient healthcare systems. Modern technologies, ranging from digital monitoring systems to data analytics and remote service delivery, have subsequently become increasingly integrated into healthcare planning and crisis preparedness. The importance of technological transformation is reinforced by evidence regarding the role of emerging technologies in crisis management [12] and by research emphasizing broader modernization of healthcare delivery systems [22]. These developments make it particularly important to evaluate whether advances in technology are ultimately associated with higher expenditure because of investment requirements or with lower expenditure because of efficiency gains.

Despite the expanding literature on the determinants of health expenditure, several gaps remain. First, a considerable proportion of prior research focuses on the average effects of explanatory variables and therefore provides limited information regarding whether relationships differ across low, medium, and high levels of health expenditure. Yet the growing use of quantile methods in research on income distribution and household health expenditure demonstrates the value of explicitly modeling distributional heterogeneity [4, 5]. Second, income inequality, relative deprivation, and technological development are frequently examined separately, even though they may jointly determine healthcare demand, access, efficiency, and expenditure. Third, emerging technologies can simultaneously affect healthcare costs, health-system efficiency, inequality, environmental sustainability, and household treatment behavior, making their net expenditure effect theoretically ambiguous [13, 16, 20]. Fourth, the Iranian health system presents a particularly relevant context because it combines persistent socioeconomic

disparities, changing patterns of urbanization and human capital, environmental pressures, technological transformation, and important constraints on public resources. Finally, the literature increasingly emphasizes the need to integrate health expenditure analysis with broader measures of accessibility, equity, institutional efficiency, environmental sustainability, and technological transformation [14, 21, 23].

Accordingly, understanding health expenditure in Iran requires an empirical framework capable of identifying heterogeneous relationships across different points of the expenditure distribution while simultaneously accounting for income inequality, relative deprivation, modern technology, and relevant macroeconomic and environmental controls. Quantile regression provides an appropriate analytical framework because it does not restrict the estimated effects to the conditional mean and can reveal whether the magnitude and direction of associations differ between relatively low and relatively high levels of health expenditure. Such an approach is particularly relevant when the effects of socioeconomic inequality and technological development are expected to be nonlinear or heterogeneous. It can therefore provide policy-relevant evidence concerning whether inequality and deprivation become increasingly consequential at higher levels of health expenditure and whether technological development contributes to expenditure reduction through greater efficiency. The resulting evidence may assist health and economic policymakers in designing targeted interventions related to income distribution, human-capital development, healthcare digitalization, environmental health, and the efficient allocation of public resources.

Therefore, the aim of the present study is to examine the quantile effects of income inequality, relative deprivation, and modern technologies on health expenditures in Iran during 1991–2024 using a quantile regression approach while controlling for the COVID-19 crisis, employment, capital formation, urban population, and CO₂ emissions.

2. Methods and Materials

The methodology of the present study is applied in terms of its objective and has applications in the health sector of the Iranian economy. In terms of its nature, the study is descriptive-analytical and falls within the category of ex post facto research.

The study hypotheses are as follows:

1. Income inequality has a positive and statistically significant effect on health expenditures in Iran.
2. Relative deprivation has a positive and statistically significant effect on health expenditures in Iran.
3. Modern technologies have a negative and statistically significant effect on health expenditures in Iran.

This study examines the quantile effects of income inequality, relative deprivation, and modern technologies on health expenditures in Iran over the period 1991–2024. Following the studies of Xiang Xu et al. (2022), Loipersberger et al. (2022), and Waheed et al. (2021), the health expenditure model is estimated using the quantile regression method. Quantile regression is a technique capable of overcoming the aforementioned limitations. These limitations include:

1. The inability to capture heterogeneity in effects across different levels of health expenditures.
2. The assumption of normally distributed error terms and homoscedasticity.
3. The inability to analyze the behavior of the dependent variable across different parts of its distribution.
4. The mean-centered nature of conventional regression and the consequent loss of distributional information.

The health expenditure model based on quantile regression, introduced by Koenker and Bassett in 1978, has gradually evolved into a comprehensive method for the statistical analysis of linear and nonlinear response-

variable models across various fields. Through quantile regression and the estimation of a family of conditional quantile functions, a more complete representation of the effects of explanatory variables across all parts of the distribution can be obtained. The principal motivation for employing quantile regression is to provide a precise and comprehensive assessment of the response variable by specifying a model in which independent variables can exert effects not only around the center of the data distribution but throughout the entire distribution, particularly in the lower and upper tails, without being constrained by the assumptions of conventional regression, heteroscedasticity, or the influential presence of outliers in coefficient estimation. In fact, quantile regression generalizes the concept of an unconditional quantile to a conditional quantile when one or more explanatory variables are present. In comparison with least-squares regression methods, in which conditional mean functions are estimated by minimizing the sum of squared residuals, quantile regression methods estimate the conditional median and a broad range of other conditional quantile functions by minimizing an asymmetrically weighted sum of the absolute values of residuals. In addition to the aforementioned characteristics, quantile regression is more robust than ordinary least squares in the presence of heteroscedasticity. The model used in this study is specified as follows:

$$Q(HE_t^{IRAN} | IQ_{1,...,n,t}) \\ = \rho_{0,q} + \beta_1 IQ_t + \beta_2 WAGEIQ_t + \beta_3 EDUIQ_t + \beta_4 ICT_t + \beta_5 COVID_t + \beta_6 L_t + \beta_7 K_t + \beta_8 POP_t + \beta_9 CO2_t \\ + \varepsilon_t$$

HE_t: Government health expenditure, including total health expenditures allocated to healthcare services (prevention and treatment), households' forward-looking arrangements for receiving such services (insurance services), nutrition, and unforeseen emergency assistance. In the present study, government public health expenditure, expressed as a percentage of current health expenditure, is used.

IQ: Income inequality, measured by the Gini coefficient, which is an indicator of inequality in the distribution of income.

Relative deprivation is measured using the Yitzhaki index (Yitzhaki, 1979), including relative deprivation in wages (*WAGEIQ*) and relative deprivation in human capital (*EDUIQ*). For this purpose, statistical data from the University of Maryland are used.

Technology Development Index (*ICT*): This index is published by the International Telecommunication Union and comprises three principal components: access, use, and skills. The index is scored on a scale from zero to ten. A higher score indicates a higher level of ICT development, whereas a lower score indicates a lower degree of ICT development in a country.

K: Gross fixed capital formation as a percentage of gross domestic product; *L*: labor employment; *CO2*: carbon dioxide emissions as a measure of air pollution.

POP: Urban population, which is the environmental variable used in this study. It represents the urbanization rate, or the proportion of the total population living in urban areas. This variable can potentially exert both positive and negative effects on health. On the positive side, urbanization enhances access to health information and healthcare services. Conversely, in addition to the higher cost of healthcare in urban areas, urbanization is associated with pollution and congestion, which adversely affect health. Considering both dimensions of urbanization, the effect of this variable on health depends on the net effect resulting from these opposing mechanisms.

COVID: The global COVID-19 crisis, for which a value of 1 is assigned to the crisis period and a value of 0 to the remaining observations. The first official report of the COVID-19 outbreak in Iran was announced on February 19, 2020.

3. Findings and Results

Initially, the stationarity of the variables included in the regression model was examined. If time series exhibit coordinated movement, such co-movement may indicate the existence of a potential long-run equilibrium relationship. In other words, if two time-series variables move together over time, it may be possible to specify a long-run equilibrium relationship between them, in which case they are said to be cointegrated. In simple terms, cointegration occurs when two time series move approximately along the same long-run trajectory. In economic analysis, it is generally assumed that variables incorporated into an economic theory maintain a long-run equilibrium relationship. In applied econometric analysis, when long-run relationships among variables are estimated, their means and variances are generally assumed to remain constant over time and independent of the time factor; consequently, behavioral stability is implicitly assumed. However, applied studies have demonstrated that, in most cases, the behavioral stability of time-series variables does not hold (Granger & Newbold, 1974; Nelson & Plosser, 1982).

Accordingly, conventional F - and t -tests obtained from estimation procedures in which behavioral stability or stationarity of the variables has not been established are invalid and may produce misleading results. This problem is known as spurious regression. Therefore, to ensure the validity of empirical findings, researchers have revised estimation procedures and systematically examined the stationarity of variables and the existence of cointegration among them.

Cointegration analysis has been regarded as one of the most revolutionary developments in econometrics since the mid-1980s. In simple terms, cointegration analysis examines the co-movement and coordinated behavior of variables, even when those variables themselves may be nonstationary and exhibit upward or downward movements over time. Their joint movement may nevertheless generate a linear long-run relationship and establish equilibrium relationships among them. Consequently, if no linear relationship exists among the variables in the long run, they are said not to be cointegrated or convergent (Engle & Granger, 1987; Johansen & Juselius, 1990).

In general, cointegration analysis is a method for estimating long-run equilibrium parameters in relationships involving nonstationary variables. It therefore constitutes a modern approach to specifying, estimating, and testing dynamic models and can consequently be used to assess the validity of economic theories. Furthermore, cointegration analysis can be used to estimate disequilibrium or short-run economic parameters because the long-run parameters obtained from cointegration analysis can be employed in estimating short-run dynamics. Such models are referred to as error correction models. Error correction models link short-run fluctuations in variables to their long-run equilibrium values.²

By definition, a time series is said to be strictly stationary, or strongly stationary, if its joint probability density function, for any given value of k , is not a function of t . Under this condition, its distribution, and consequently its moments including the mean and variance, are independent of time.³

However, examining strict stationarity in practice is complex, and time-series analyses generally do not require the strong-stationarity assumption. Instead, stationarity in the weak sense is typically considered.

A time series is said to be weakly stationary if the relevant stationarity conditions concerning its mean, variance, and autocovariance function are satisfied.

As can be observed, the mean of the time series must remain constant, and its autocovariance function for every specified value of k must not depend on t . For this reason, a weakly stationary time series is also referred to as covariance stationary. It should also be noted that the variance of the time series must be independent of time. Hereafter, the term “stationarity” refers to weak stationarity.

The importance of stationarity in economics lies in the fact that a stationary series does not retain the effect of a shock indefinitely. If a shock affects such a series, its effect is not permanent and eventually dissipates.

This issue is particularly important in cointegration analysis.

Nonstationary time series may arise in two ways. In the first case, the series x_t is a function of the time variable t , generally represented as a deterministic trend process in which the disturbance term is stationary.

When the deterministic component is a first-degree polynomial in time, the series may be represented generally as:

$$x_t = \alpha + \beta t + u_t \quad (1)$$

where u_t is a stationary disturbance term.

The mean of x_t is a function of time and is therefore nonstationary. In the second case, x_t is generated by a stochastic process of the following general form:

$$x_t = \alpha + x_{t-1} + u_t \quad (2)$$

where u_t is a stationary series with zero mean and constant variance. The above model is known as a random-walk process.¹ Through successive substitution and assuming that x_0 is known, the process may be represented as:

$$x_t = x_0 + \alpha t + \sum_{i=1}^t u_i \quad (3)$$

In this case, the variance of x_t is not independent of time. Nevertheless, both models (1) and (2) exhibit a linear trend. In model (1), u_t represents a temporary shock, whereas in model (2), it represents a permanent shock.

If an economic variable is affected by permanent shocks, model (2) is applied to that variable. Models (1) and (2) are respectively referred to as the deterministic-trend model and the stochastic-trend model. In both models, x_t increases at a particular rate. If x_t is expressed in logarithmic form, the relevant coefficient can be interpreted as its growth rate. However, shocks are temporary in the first model and permanent in the second. The constant growth component in the second model is referred to as the drift term or trend term. Unlike stochastic trends, deterministic trends do not create difficulties for valid statistical inference and cointegration analysis. Their effects need only be controlled for by including the trend term t in the model. Accordingly, cointegration analysis is primarily concerned with stochastic trends.

For certain purposes, it may be desirable to detrend time series. For this purpose, x_t can be regressed on time, in which case the residuals obtained from this regression will be trend-free. Alternatively, differencing can be used to obtain a stationary series as follows:

$$\Delta x_t = x_t - x_{t-1} \quad (4)$$

In the stochastic-trend model, first differencing can likewise produce a stationary series because:

$$\Delta x_t = \alpha + u_t \quad (5)$$

Model (4) is referred to as a trend-stationary process, whereas model (5) is referred to as a difference-stationary process. This terminology was introduced by Nelson and Plosser.

Cointegration analyses are concerned with difference-stationary processes (DSPs), that is, processes that become stationary after differencing.

For this purpose, the relevant time-series equations can be considered under the assumption that their disturbance terms are independently and identically distributed.

To examine stationarity, the null hypothesis of nonstationarity (H_0) and the alternative hypothesis of stationarity (H_1) are considered.

If the relevant unit-root parameter indicates the presence of a unit root, the series is nonstationary. If the null hypothesis of nonstationarity is rejected, the series is said to be integrated of order zero:

$$I(0)$$

If the series is nonstationary, differencing may be used to render it stationary. If it becomes stationary after first differencing, it is said to be integrated of order one:

$$I(1)$$

More generally, if a series becomes stationary after being differenced d times, it is said to be integrated of order d :

$$I(d)$$

If k time series,

$$x_{1t}, x_{2t}, \dots, x_{kt},$$

are integrated of order d , and there exists a linear combination among them that is integrated of a lower order, they are said to be cointegrated of order (d, b) , provided that $b > 0$. In general notation:

$$x_t \sim CI(d, b)$$

where an appropriate linear combination of the variables is integrated of order:

$$I(d - b)$$

If several time series are integrated at different orders, their linear combination will generally be integrated at the highest order of integration. In the present study, the Phillips–Perron test was used to examine the stationarity of the variables.

Table 1. Results of the Phillips–Perron Test for the Model Variables

Variable	Test Statistic	Probability	Variable Status
WAGEIQ	0.469	0.811	–
D(WAGEIQ)	–9.324	0.000	$I(1)$
CO2	–1.864	0.344	–
D(CO2)	–6.346	0.000	$I(1)$
COVID	–2.549	0.114	–
D(COVID)	–5.491	0.0001	$I(1)$
EDUIQ	–2.689	0.247	–
D(EDUIQ)	–8.433	0.000	$I(1)$

HE	-3.083	0.127	–	
D(HE)	-8.393	0.000		$I(1)$
ICT	-1.677	0.366	–	
D(ICT)	-9.311	0.000		$I(1)$
IQ	-0.687	0.412	–	
D(IQ)	-10.119	0.000		$I(1)$
K	-0.532	0.479	–	
D(K)	-8.731	0.000		$I(1)$
L	-1.582	0.117	–	
D(L)	-10.741	0.000		$I(1)$
POP	-1.3698	0.155	–	
D(POP)	-8.889	0.000		$I(1)$

According to the results of the stationarity tests for the model variables, all variables become stationary after first differencing and are therefore integrated of order one, $I(1)$.

Two major techniques are available for examining cointegration: the Engle–Granger method and the Johansen–Juselius method. The Engle–Granger procedure examines the existence of only one long-run relationship among two or more variables. When the number of variables exceeds two, this method encounters difficulties in identifying long-run relationships because only one error component is incorporated into the equation (Nowferesti, 2008). Furthermore, some information is lost through differencing. The Johansen–Juselius method has several advantages over other cointegration tests. One advantage is that it does not rely on differencing to make the variables stationary because differencing can eliminate the long-run equilibrium properties among the variables. By calculating the error-correction component and incorporating it into equations formulated in differences, this method allows long-run equilibrium properties to be retained. It also enables the identification and estimation of cointegrating vectors, that is, the coefficients associated with long-run equilibrium relationships among the variables. The relationship between the model and cointegration makes it possible to derive the cointegrating vectors directly from the coefficients of the vector autoregressive model (Nowferesti, 1999). In the Johansen–Juselius cointegration procedure used to examine the existence of long-run relationships among the model variables, the first step is to determine precisely the order of integration of the variables (Johansen & Juselius, 1991). After the order of integration has been established and cointegration among the model variables has been confirmed, the second stage consists of estimating the long-run relationships and the cointegrating vector or vectors.

Based on the Johansen–Juselius procedure, the trace test (λ_{Trace}) and maximum-eigenvalue test (λ_{max}) were used to determine the number of cointegrating vectors. As shown in Table 2, according to the λ_{Trace} test, the null hypothesis that no cointegrating vector exists is rejected, whereas the alternative hypothesis indicating the presence of more than one cointegrating vector is supported. The difference between the λ_{max} and λ_{Trace} statistics is that the alternative hypothesis in the λ_{max} test is more specifically defined. The results of the λ_{max} and λ_{Trace} tests may occasionally be inconsistent. In fact, the λ_{max} test has a more explicit and specific alternative hypothesis. Nevertheless, when contradictory results arise, selecting the smaller number of cointegrating vectors is generally preferable (Enders, 2007). The results are presented in Table 2.

Table 2. λ_{Trace} and λ_{max} Cointegration Tests

Unrestricted Cointegration Rank Test: Trace				
Hypothesized Number of Cointegrating Equations	Eigenvalue	Trace Statistic	0.05 Critical Value	Probability
None *	0.994	525.058	239.235	0.000
At most 1 *	0.973	361.327	197.371	0.000
At most 2 *	0.946	245.844	159.529	0.000
At most 3 *	0.822	152.645	125.615	0.0004
At most 4 *	0.675	97.434	95.754	0.038
At most 5	0.517	61.513	69.819	0.192
At most 6	0.439	38.224	47.856	0.292
At most 7	0.390	19.671	29.797	0.445
At most 8	0.113	3.832	15.495	0.917
At most 9	0.0001	0.004	3.841	0.949
Unrestricted Cointegration Rank Test: Maximum Eigenvalue				
Hypothesized Number of Cointegrating Equations	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Probability
None *	0.994	163.731	64.504	0.000
At most 1 *	0.973	115.484	58.434	0.000
At most 2 *	0.946	93.198	52.363	0.000
At most 3 *	0.822	55.211	46.231	0.004
At most 4	0.675	35.921	40.078	0.137
At most 5	0.517	23.288	33.877	0.508
At most 6	0.439	18.554	27.584	0.449
At most 7	0.390	15.839	21.132	0.234
At most 8	0.113	3.828	14.265	0.877
At most 9	0.0001	0.003	3.841	0.949

In both tests, the hypothesis that at least four cointegrating vectors exist is supported.

Engle and Granger (1987) stated that if the Dickey–Fuller test is applied to the residuals of a model and the residual time series is found to be stationary, this provides evidence of cointegration. However, caution must be exercised when using this procedure because the conventional critical values are not fully appropriate, and the Engle–Granger critical values should instead be used. Under this approach, stationarity and nonstationarity are examined using the Dickey–Fuller unit-root test. The hypotheses are specified as follows:

H_0 : No cointegration

H_1 : Cointegration

The results of the test are reported in Table 3.

Table 3. Engle–Granger Cointegration Test

Test Statistic	Probability
-2.441	0.0221

In this section, the conditional probability distributions of health expenditures are derived through quantile regression, and the effects of the explanatory variables on these distributions are examined. Particular emphasis is placed on identifying the effects of income inequality, relative deprivation, and modern technologies, together with the other explanatory variables, in the lower and upper parts of the health expenditure distribution in Iran. The results obtained from estimating the model using the quantile regression method are reported in Table 4.

Table 4. Long-Run Coefficient Estimates from the Quantile Regression Model: Health Expenditure Model, 1991–2024

Variable	Q-Reg (25) Coefficient (p-value)	Q-Reg (50) Coefficient (p-value)	Q-Reg (75) Coefficient (p-value)	Q-Reg (95) Coefficient (p-value)
C	0.264 (0.042)	0.174 (0.036)	0.621 (0.021)	0.534 (0.011)
IQ	0.365 (0.044)	0.415 (0.032)	0.453 (0.021)	0.498 (0.0001)
WAGEIQ	0.177 (0.049)	0.256 (0.037)	0.275 (0.026)	0.296 (0.018)
EDUIQ	0.119 (0.044)	0.454 (0.033)	0.956 (0.024)	0.996 (0.002)
ICT	-0.464 (0.0423)	-0.556 (0.0315)	-0.568 (0.026)	-0.753 (0.016)
COVID	0.170 (0.039)	0.256 (0.027)	0.526 (0.018)	0.558 (0.003)
L	-0.256 (0.040)	-0.314 (0.032)	-0.371 (0.011)	-0.411 (0.0001)
K	-0.160 (0.043)	-0.213 (0.041)	-0.871 (0.035)	-0.991 (0.002)
POP	0.301 (0.099)	0.313 (0.081)	0.889 (0.0610)	0.936 (0.041)
CO2	0.171 (0.047)	0.305 (0.033)	0.802 (0.0200)	0.945 (0.0009)

The quantile regression results presented in Table 4 indicate that, at the first and second lower quantiles, income inequality has a positive and statistically significant effect on health expenditures, and the magnitude of this effect increases as the model moves toward the third and fourth quantiles. In other words, at the first quantile (Q_{25}) and the second quantile (Q_{50}), the income inequality index exhibits a positive temporal association with health expenditures. As the analysis moves toward the third quantile (Q_{75}) and the fourth quantile (Q_{95}), the association between the income inequality index and health expenditures becomes stronger.

The first hypothesis is specified as follows:

H_0 : Income inequality has no statistically significant effect on health expenditures in Iran.

H_1 : Income inequality has a statistically significant effect on health expenditures in Iran.

According to the calculated probability values for the *IQ* variable at the first (Q_{25}), second (Q_{50}), third (Q_{75}), and fourth (Q_{95}) quantiles of the health expenditure model, all of which are below 0.05, the null hypothesis is rejected. It can therefore be concluded that the quantile effects of income inequality on health expenditures in Iran are positive and statistically significant.

The second hypothesis is specified as follows:

H_0 : Relative deprivation has no statistically significant effect on health expenditures in Iran.

H_1 : Relative deprivation has a statistically significant effect on health expenditures in Iran.

According to the calculated probability values for the *WAGEIQ* and *EDUIQ* variables at the first (Q_{25}), second (Q_{50}), third (Q_{75}), and fourth (Q_{95}) quantiles of the health expenditure model, all of which are below 0.05, the null hypothesis is rejected. It can therefore be concluded that the quantile effects of relative deprivation on health expenditures in Iran are positive and statistically significant.

The third hypothesis is specified as follows:

H_0 : Modern technologies have no statistically significant effect on health expenditures in Iran.

H_1 : Modern technologies have a statistically significant effect on health expenditures in Iran.

According to the calculated probability values for the *ICT* variable at the first (Q_{25}), second (Q_{50}), third (Q_{75}), and fourth (Q_{95}) quantiles of the health expenditure model, all of which are below 0.05, the null hypothesis is rejected.

It can therefore be concluded that the quantile effects of modern technologies on health expenditures in Iran are negative and statistically significant.

4. Discussion and Conclusion

The present study examined the quantile effects of income inequality, relative deprivation, and modern technologies on health expenditures in Iran over the period 1991–2024. The findings provide clear evidence that the determinants of health expenditure are heterogeneous across different points of the expenditure distribution and therefore cannot be adequately represented by approaches that focus exclusively on conditional mean effects. The quantile regression estimates indicated that income inequality exerted a positive and statistically significant effect on health expenditures at all estimated quantiles, with the magnitude of the coefficient increasing progressively from 0.365 at Q_{25} to 0.415 at Q_{50} , 0.453 at Q_{75} , and 0.498 at Q_{95} . Relative deprivation displayed a similar pattern. Wage-related relative deprivation had positive and significant coefficients of 0.177, 0.256, 0.275, and 0.296 across the four quantiles, while relative deprivation in human capital increased substantially from 0.119 at Q_{25} to 0.996 at Q_{95} . In contrast, ICT development had a negative and significant effect on health expenditures throughout the distribution, with the absolute magnitude of its coefficient increasing from -0.464 at the lower quantile to -0.753 at the highest quantile. These findings confirm that socioeconomic inequality and deprivation place increasingly greater pressure on health expenditures at higher expenditure levels, whereas technological development may play an increasingly important expenditure-reducing role as health expenditure rises.

The positive relationship between income inequality and health expenditure is consistent with the theoretical proposition that unequal distribution of economic resources can generate unequal exposure to health risks, weaken access to preventive services among disadvantaged groups, and eventually increase demand for costly treatment and public healthcare interventions. The increasing magnitude of the income inequality coefficient across quantiles is particularly important because it suggests that inequality becomes more consequential in periods or conditions characterized by relatively high health expenditure. This finding is closely aligned with recent quantile-based evidence from Iran showing that income inequality and relative deprivation are important determinants of household health expenditures and that their effects differ across expenditure quantiles [5]. It is also compatible with evidence showing that socioeconomic inequality affects population health heterogeneously rather than uniformly across groups and conditions [6]. The result can therefore be interpreted as indicating that income inequality does not merely increase average healthcare demand; rather, its adverse health and financial consequences become stronger toward the upper end of the health expenditure distribution.

This result is also consistent with studies emphasizing the broader relationship between income distribution and health-system financing. Research on Iranian provinces has shown that disparities in socioeconomic conditions are associated with health inequality, supporting the argument that unequal economic opportunities can translate into unequal health outcomes and healthcare needs [2]. From another perspective, health expenditures themselves may influence income distribution, indicating a two-way relationship between inequality and health financing [3]. The present findings contribute to this literature by demonstrating that the reverse direction is also important: higher income inequality is associated with higher health expenditure, particularly in the upper quantiles. This relationship may operate through greater prevalence of chronic illness among disadvantaged groups, delayed utilization of healthcare, lower preventive investment, and increased reliance on expensive treatment after disease progression. Inequality in out-of-pocket healthcare payments and differences in financial protection similarly indicate that unequal access to resources can directly shape healthcare utilization and financial burden [8].

Moreover, because medical expenditures can substantially affect measured poverty and disposable household resources, especially among vulnerable groups, the observed relationship between inequality and health expenditure is likely to be embedded within a broader cycle linking poverty, healthcare needs, and financial vulnerability [7].

The second major finding concerns relative deprivation. Both wage-related deprivation and deprivation in human capital had positive and statistically significant effects on health expenditures across all quantiles. However, the coefficient for human-capital deprivation increased much more sharply across the distribution. This pattern suggests that relative disadvantage in education, skills, knowledge, and other dimensions of human capital may become particularly costly when health expenditure is already high. A plausible explanation is that lower human capital is associated with weaker health literacy, less effective use of preventive services, delayed diagnosis, poorer adherence to treatment, and reduced ability to navigate complex healthcare systems. These mechanisms can increase dependence on more expensive curative care. Wage deprivation may operate through a parallel mechanism by limiting access to healthy food, appropriate housing, preventive medical services, and other health-enhancing resources. The findings are again consistent with quantile evidence indicating that relative deprivation contributes to variation in health expenditures in Iran [5]. They are also compatible with the broader evidence that determinants of income distribution in Iranian urban areas vary across quantiles, highlighting the importance of distribution-sensitive socioeconomic analysis [4].

The particularly strong effect of human-capital deprivation at higher quantiles may also be interpreted in relation to inequality in access to modern healthcare. As medical systems become more technologically complex, the ability to obtain, understand, and appropriately use health information becomes increasingly important. Digitalization can improve access for some groups but may widen inequalities for individuals with lower educational attainment, weaker digital literacy, or inadequate technological access [21]. Therefore, the interaction between human-capital deprivation and technological transformation may partly explain why educationally disadvantaged populations experience disproportionately high healthcare costs. Access inequality is also relevant to emerging health technologies because differences in access can change household treatment expenditure patterns and influence who benefits from cost-saving innovations [16]. The present findings therefore suggest that technological progress alone may not eliminate expenditure inequality unless accompanied by policies addressing education, digital competence, and equitable access.

The third principal finding was the negative and statistically significant effect of ICT development on health expenditures. The magnitude of the coefficient became increasingly negative at higher quantiles, suggesting that the expenditure-reducing effect of ICT may be strongest when health spending is relatively high. This result can be explained by several efficiency channels. Digital technologies may reduce administrative costs, improve scheduling and patient flow, facilitate electronic health information exchange, prevent unnecessary duplication of diagnostic procedures, support remote care, enhance disease monitoring, and improve resource allocation. Evidence from developing countries has shown that ICT is significantly related to health expenditures and can influence healthcare costs alongside broader economic factors [15]. Evidence from public-sector healthcare management similarly indicates that information technology is linked with the effectiveness of public management and patterns of health expenditure [14]. The present study strengthens these findings by showing that ICT is associated with lower public health expenditure across the entire conditional distribution and that this relationship intensifies in the upper expenditure quantiles.

The observed negative relationship between ICT and health expenditures is also consistent with the broader literature on emerging technologies in healthcare. New technologies can improve diagnostic accuracy, accelerate clinical decision-making, facilitate preventive intervention, and support more efficient healthcare delivery [9]. Artificial intelligence can increase processing capacity and assist primary medical services, potentially reducing delays and improving the efficiency of clinical decisions [18]. Technologies based on biomarkers and advanced diagnostic methods may create cost savings by enabling earlier and more targeted interventions [17]. Emerging technologies are also increasingly important for crisis management in hospitals and healthcare centers, where rapid access to information and coordinated resource allocation can reduce unnecessary costs during periods of elevated demand [12]. The increasing absolute magnitude of the ICT coefficient across quantiles may therefore indicate that technology becomes especially valuable where health systems face greater expenditure pressures.

Nevertheless, the finding should not be interpreted to mean that all technological adoption automatically reduces expenditure. Technology itself requires investment in infrastructure, software, training, maintenance, cybersecurity, and organizational change. Hospitals differ substantially in their information technology expenditures, and meaningful cross-institutional comparison requires careful measurement of such investments [13]. Furthermore, the healthcare supply chain faces several organizational and managerial considerations when selecting emerging technologies [10]. Thus, the negative long-run relationship observed in the present study may reflect net efficiency gains after the initial costs of adoption are absorbed. This interpretation is reinforced by research emphasizing technical efficiency and managerial capability in Iran's health sector [23] and by evidence that performance differences among health centers can be substantial when effectiveness and resource use are jointly evaluated [24]. Technology is therefore likely to reduce health expenditure when it is integrated into efficient organizational and managerial systems rather than simply added as an additional layer of cost.

The results for the control variables also provide important insights. The COVID-19 variable was positive and statistically significant across all quantiles, with its coefficient increasing from 0.170 at Q_{25} to 0.558 at Q_{95} . This result is expected because the pandemic generated exceptional demand for hospitalization, diagnostic testing, protective equipment, vaccination infrastructure, emergency staffing, and other healthcare services. Its stronger effect in the upper expenditure quantiles suggests that the fiscal consequences of health crises are particularly pronounced when health systems are already operating under high expenditure conditions. This interpretation is consistent with the increasing emphasis on technological transformation and crisis preparedness within modern healthcare systems [12, 22]. It also reinforces the importance of developing resilient healthcare infrastructures capable of managing exceptional demand without disproportionately increasing costs.

Employment had a negative and statistically significant relationship with health expenditures at all quantiles, and its negative effect strengthened toward the upper part of the distribution. One explanation is that higher employment improves household income security, access to employer-based or contributory insurance mechanisms, and general socioeconomic conditions, thereby reducing some forms of dependence on government-financed healthcare. Employment may also improve the ability to invest in preventive care and healthier living conditions. Similarly, gross fixed capital formation had a negative and significant effect, with a particularly large coefficient at the highest quantile. Capital formation may improve economic infrastructure, productivity, and the fiscal capacity of the economy, thereby indirectly reducing health-related vulnerabilities or improving the efficiency of service provision. Because financial and real-sector developments can influence healthcare markets, the broader economic environment remains relevant to health-sector expenditure dynamics [25].

Urban population had positive coefficients across all quantiles, although statistical significance was reached only at the highest quantile. This pattern suggests that urbanization may become a significant driver of public health expenditure mainly when expenditure is already high. Urban areas generally provide better access to healthcare facilities, specialist services, and diagnostic technologies, which can increase utilization. At the same time, urbanization is frequently associated with congestion, sedentary lifestyles, pollution, and environmental stressors that may increase morbidity. The positive association between urbanization-related pressures and healthcare costs has been documented in research emphasizing the joint roles of urbanization, environmental quality, economic growth, and other structural factors in determining healthcare expenditure [26]. The absence of significance at lower quantiles may indicate that positive and negative urbanization effects partially offset each other until health expenditure reaches sufficiently high levels.

Finally, CO_2 emissions had a positive and statistically significant effect on health expenditures at all quantiles, with the coefficient rising sharply from 0.171 at Q_{25} to 0.945 at Q_{95} . This is one of the strongest distributional patterns observed in the model and indicates that environmental deterioration increasingly contributes to health expenditure at higher expenditure levels. Greater carbon emissions are generally associated with industrialization, fossil-fuel dependence, air pollution, and urban environmental pressures, all of which may increase the incidence of respiratory, cardiovascular, and other pollution-related health conditions. The result is consistent with evidence demonstrating complex relationships among environmental quality, energy use, urbanization, industrialization, and healthcare costs [26]. It also aligns with findings showing that CO_2 emissions and health expenditures jointly influence quality-of-life outcomes [27]. Sustainable healthcare technologies and improved medical waste management may therefore have implications beyond environmental protection by potentially reducing future healthcare burdens associated with environmental degradation [20]. Similarly, the growth of sustainable and green healthcare technologies may support the transition toward healthcare systems that are simultaneously more efficient and environmentally responsible [11, 19].

The present study has several limitations that should be considered when interpreting its findings. First, the analysis relies on annual macroeconomic time-series data for Iran, which limits the number of observations and may reduce the ability to identify short-term structural changes with high precision. Second, several constructs, particularly relative deprivation and technological development, are represented through aggregate indicators that may not fully capture differences across households, provinces, income groups, or healthcare institutions. Third, the ICT index reflects broad technological development and does not distinguish among specific technologies such as telemedicine, electronic health records, artificial intelligence, digital diagnostics, or hospital information systems. Fourth, although the model includes several important control variables, health expenditures may also be influenced by demographic aging, disease prevalence, insurance coverage, pharmaceutical prices, physician density, fiscal policy, sanctions, and other institutional factors not explicitly incorporated into the model. Fifth, the COVID-19 crisis is modeled using a dummy variable, which captures the existence of the crisis but not differences in its severity across time. Finally, quantile regression identifies heterogeneous conditional associations but does not by itself establish strict causal relationships between the explanatory variables and health expenditures.

Future studies could extend the present analysis by using provincial or household-level panel data to examine whether the relationships identified at the national level vary across regions, income classes, demographic groups, and levels of healthcare access. Researchers could also decompose technological development into specific dimensions, including telemedicine, artificial intelligence, electronic health records, mobile health applications, digital insurance systems, and hospital automation, to determine which technologies generate the greatest

expenditure-saving effects. Future research may incorporate interaction terms between income inequality, human-capital deprivation, and ICT to test whether technological development moderates the adverse effects of socioeconomic inequality on health expenditure. Nonlinear and dynamic methods, including panel quantile regression, quantile-on-quantile regression, nonlinear ARDL models, and time-varying parameter models, could provide additional evidence regarding asymmetric and changing relationships over time. It would also be useful to incorporate demographic aging, chronic disease prevalence, insurance coverage, healthcare workforce indicators, pharmaceutical expenditure, environmental pollution measures beyond CO_2 , and institutional quality. Comparative analyses between Iran and countries with similar income levels or health-system structures could further clarify which findings are country-specific and which reflect broader structural patterns.

The findings suggest that health and economic policymakers should treat inequality reduction, human-capital improvement, digital transformation, and environmental protection as complementary components of health-expenditure management. Policies designed to reduce income inequality and relative deprivation may help control future healthcare costs by improving access to preventive services, health literacy, nutrition, and other social determinants of health before costly medical interventions become necessary. Investment in ICT should prioritize technologies that demonstrably improve service efficiency, reduce duplication, strengthen preventive care, and facilitate remote access, while ensuring that low-income and low-literacy groups are not excluded by the digital divide. Health authorities should also expand digital literacy programs for patients and healthcare workers and evaluate technological investments on the basis of measurable efficiency and expenditure outcomes. Employment-supporting and productive investment policies may generate indirect health benefits and reduce pressure on public health budgets. Finally, environmental and urban policies should be coordinated with health-sector planning, particularly through stronger air-pollution control, cleaner energy use, sustainable urban development, and systematic assessment of the health costs of environmental degradation.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

Acknowledgments

Authors thank all participants who participate in this study.

Conflict of Interest

The authors report no conflict of interest.

Funding/Financial Support

According to the authors, this article has no financial support.

References

- [1] M. Hartman, A. Martin, and B. Washington, "National Health Care Spending Growth and Its Implications," 2025. [Online]. Available: <https://link.springer.com/article/10.1007/s11205-023-03204-8>.
- [2] A. A. Salem, E. Jahangard, and L. Jabbari, "Factors Affecting Health Inequality in Iranian Provinces," *Journal of Management and Health*, vol. 11, no. 58, pp. 121-135, 2021.
- [3] M. Ameli, A. Ghiasvand, and M. Hadi Nejad, "The Impact of Health Expenditures on Income Inequality in Selected Member Countries of the Organisation of Islamic Cooperation," *Financial Economics Quarterly*, vol. 11, no. 2, pp. 325-328, 2024.
- [4] S. Jamal Shargh, A. A. Khosravinejad, G. Geraeinejad, and M. R. Mirzaeinejad, "Examining the Effects of Factors Influencing Income Distribution in Urban Areas of Iranian Provinces: A Quantile Panel Approach," *Quarterly Journal of Applied Economic Theories*, vol. 8, no. 28, pp. 323-338, 2021.
- [5] A. Zare, M. Ghorbani, and M. Ghanbari, "Quantile Analysis of the Effects of Income Inequality and Relative Deprivation on Health Expenditures of Urban Households in Iran," *Quarterly Journal of Health Economic Research*, vol. 10, no. 1, pp. 45-70, 2026.
- [6] Z. Wang and Q. Li, "Heterogeneous Influence of Socioeconomic Inequality on Population Health," 2023. [Online]. Available: <https://www.tandfonline.com/doi/full/10.1080/01603477.2024.2334453>.
- [7] B. Meyer and J. Sullivan, "Medical Expenditures and the Measurement of Poverty," 2024. [Online]. Available: <https://www.mdpi.com/2227-9032/12/10/1051>.
- [8] Y. Li, X. Zhang, and H. Chen, "Inequalities in Out-of-Pocket Health Expenditure and Universal Health Coverage," ed, 2024.
- [9] M. Dehghani and M. H. Afrazeh, "The Role of Emerging Technologies in Improving Healthcare Services," Astara, 2025.
- [10] H. Eghbali, E. Tavangar, and Z. Nematollahi, "Identifying Factors Affecting the Selection of Emerging Technologies in the Healthcare Supply Chain," Ardabil, 2024.
- [11] A. Ziyamehr, "Application of Emerging Technologies in Medical and Biological Sciences," 2025.
- [12] A. Seifi Ardali and M. Azarbarzin, "The Role of Emerging Technologies in Managing Hospital and Healthcare Center Crises," Tehran, 2025.
- [13] L. L. Reincke and J. D. Liebe, "Measuring Information Technology Expenditures of Hospitals for Cross-Institutional Comparisons: A Scoping Review," *International Journal of Medical Informatics*, vol. 202, p. 105968, 2025, doi: 10.1016/j.ijmedinf.2025.105968.
- [14] L. M. G. Franco, A. G. d. Oliveira, P. D. R. Silva, and A. Zucchi, "Information Technology, Public Management Effectiveness Index and Health Expenditures: A Study with Municipalities in the State of Parana," *Procedia Computer Science*, vol. 256, no. 1302, p. 1309, 2025, doi: 10.1016/j.procs.2025.01.150.
- [15] S. Safrazadeh, "The Impact of Information and Communication Technology and Renewable Energy on Health Expenditures with Emphasis on Economic Openness in Developing Countries," 2021.
- [16] S. Mousavi and F. Safarian, "The Role of Emerging Health Technologies in Changing Household Treatment Spending Patterns: A Difference-in-Access Approach," *Iranian Journal of Information Technology in Health Systems*, vol. 6, no. 2, pp. 25-48, 2026.
- [17] R. Ahnyne *et al.*, "Critical Analysis of the Cost Savings Generated by Biomarkers and Oncoviruses in Healthcare," 2026, pp. 309-326.
- [18] N. a.-D. Nahasi, "Examining the Right to Health and the Use of Artificial Intelligence's Assistance Potential and Processing Speed in Primary Medical Services," Tehran, 2023.
- [19] S. Athimoolam, S. B. Ahamed, B. N. R. Kumar, and V. Kalyanasundaram, "Green Flexible Electronics for Sustainable Healthcare: Market Size of Green Flexible Electronics for Healthcare Ecosystem in Modern Era," 2026, pp. 79-97.
- [20] H. Nematollahi, M. Tuysserkani, and A. Nematollahi, "Medical Waste Management in the Modern Healthcare Era: A Comprehensive Review of Technologies, Environmental Impact, and Sustainable Practices," *Results in Engineering*, vol. 28, p. 107210, 2025.
- [21] J. Badr, A. Motulsky, and J. L. Denis, "Digital Health Technologies and Inequalities: A Scoping Review of Potential Impacts and Policy Recommendations," *Health Policy*, vol. 146, p. 105122, 2024, doi: 10.1016/j.healthpol.2024.105122.
- [22] A. Alharbi, M. Aljuaid, F. A. Alamri, S. N. Alosaimi, and S. Aldeijy, "Health Sector Transformation in Saudi Arabia—The Modern Healthcare Model: A Qualitative Study among Healthcare Leaders," *Journal of Taibah University Medical Sciences*, vol. 20, no. 5, pp. 643-653, 2025, doi: 10.1016/j.jtumed.2025.10.005.
- [23] S. Safarpour, A. Amirtaymouri, S. Kordrostami, and L. Khoshandam, "Analysis of Technical Efficiency and Managerial Capability in Iran's Health Sector," *Industrial Management Studies*, vol. 22, no. 72, pp. 37-72, 2024.
- [24] M. R. Shahari, K. F. See, N. S. Mohammed, and M.-M. Yu, "Constructing the Performance Index of Malaysia's District Health Centers Using Effectiveness-Based Hierarchical Data Envelopment Analysis," *Socio-Economic Planning Sciences*, vol. 89, p. 101662, 2023, doi: 10.1016/j.seps.2023.101662.

- [25] S. Khodaeinejad, M. Zaenderoudi, and S. A. Jalaei Esfandabadi, "Examining Price Bubbles in the Healthcare Sector of the Tehran Stock Exchange," *Financial Economics Quarterly*, no. 145, pp. 39-61, 2020.
- [26] A. Raihan, M. Ridwan, S. M. Rahman, and T. Sarker, "Navigating the Complexities of Healthcare Costs in Bangladesh: A Closer Look at Environmental Quality, Economic Growth, Energy Use, Industrialization, Urbanization, and Forest Area," *Innovation and Green Development*, vol. 5, no. 1, p. 100328, 2026.
- [27] N. O. Beser, M. Cabas, S. Ugurlu, and C. Magazzino, "The Determinants of Life Quality in African Countries: Moderating Role of CO2 Emissions and Health Expenditures," *Green Technologies and Sustainability*, vol. 3, no. 3, p. 100165, 2025, doi: 10.1016/j.gts.2025.100165.