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Examining the Relationship Between Healthcare Infrastructure and Public Health in Iran Using a Structural Approach Model

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ABSTRACT

The present study aims to examine the relationship between healthcare infrastructure and public health in Iran. The importance of this issue lies in the fact that efficient healthcare infrastructures—including medical facilities, equipment, and specialized human resources—provide the foundation for improving service quality, enhancing equitable access to care, and ultimately reducing the financial burden on the health system. At a time when the disease pattern has shifted from communicable diseases toward non-communicable and chronic conditions, significantly increasing healthcare expenditures, analyzing the impact of healthcare infrastructure on key health indicators has become increasingly critical. To achieve this objective, a structural model was employed, enabling the examination of long-term relationships among the main variables in the health sector. The model was designed to analyze both private and public sector investments in healthcare and to assess their effects on indicators such as life expectancy and mortality rates. In addition, the role of other factors—including the number of hospitals, physicians, nurses, and specialized healthcare personnel—was incorporated into the model in order to present a comprehensive depiction of the relationship between healthcare infrastructure and public health. The results indicate that the development of healthcare infrastructure, particularly private sector investment, has the strongest positive impact on improving public health indicators, specifically by increasing life expectancy and reducing mortality rates. Public investment also exerts a significant effect on improving these indicators; however, its contribution is smaller compared to that of the private sector. Furthermore, strengthening human resources in the health sector—including physicians, nurses, and midwives—plays a meaningful role in enhancing public health outcomes. Conversely, variables such as population size and literacy rate, contrary to expectations, did not show a substantial effect on the indicators under investigation. Additional analyses revealed that the stability of the model and the increasing share of private investment over time underscore the necessity of paying particular attention to this domain.

Keywords: *Life expectancy; Mortality rate; Private healthcare investment; Healthcare infrastructure*

1. Introduction

Healthcare systems are increasingly treated not only as social welfare institutions but also as productivity-enhancing infrastructures that shape national development trajectories. Contemporary policy debates emphasize that public health outcomes—such as life expectancy and mortality—are co-produced by physical infrastructure (hospitals, beds, medical technology), human resources (physicians, nurses, midwives), and the financing architecture that determines investment capacity and allocative efficiency. In developing and middle-income economies, these determinants are further conditioned by fiscal constraints, macroeconomic volatility, and institutional features that influence how resources translate into service coverage and population-level health gains. From a management and policy perspective, therefore, the central question is no longer whether health spending matters, but under what structural conditions investments in health infrastructure and workforce generate sustained improvements in public health indicators and broader socioeconomic performance (Das & Guha, 2024; Gaies, 2022; Mbau et al., 2023).

A foundational lens for understanding these relationships is the concept of health as capital, which frames health as a durable stock that produces utility directly and also enhances individuals' productive time and earnings potential. In this view, investments in prevention, care access, and service quality can be interpreted as investments that expand a society's effective labor supply and reduce economic losses from morbidity and premature mortality. This theoretical framing provides a coherent bridge between public health and management research: it links resource allocation decisions—by governments and private actors—to measurable outcomes in human development and economic growth. It also highlights why infrastructure and staffing are central rather than peripheral: when capacity constraints exist (limited beds, shortages of skilled personnel, under-equipped facilities), marginal increases in financing may not translate into proportional improvements in outcomes. Consequently, empirical models that incorporate both financial inputs and capacity variables are better aligned with the health-capital framework and the operational realities of healthcare delivery (Grossman, 2017; Ogundari & Awokuse, 2018; Ying et al., 2022).

Within this broader paradigm, the role of health expenditure and investment is frequently examined through two complementary channels. The first is the "public financing" channel, whereby government expenditure improves access, reduces out-of-pocket spending pressure, and mitigates interregional and socioeconomic inequalities in health outcomes. Cross-country and multicountry evidence indicates that public spending can reduce inequities in infant and overall mortality, particularly in low- and middle-income contexts where baseline service access is uneven. The second channel is the "system capacity and efficiency" channel, which emphasizes that the same expenditure can produce different outcomes depending on governance quality, managerial capabilities, and operational efficiency. Systematic assessments of health system efficiency demonstrate that resource-to-outcome conversion varies widely across settings, suggesting that spending levels alone are insufficient to explain improvements in population health. Therefore, a management-oriented empirical approach should test not only the magnitude of spending (public and private) but also the structural pathways through which spending, infrastructure, and workforce jointly affect health indicators (Akinkugbe & Mamotlohi, 2020; Baker et al., 2019; Gaies, 2022; Mbau et al., 2023).

The Iranian context makes these issues particularly salient. Iran has pursued successive reforms aimed at expanding coverage and strengthening service provision; however, the system continues to face pressures from epidemiological transition and rising costs associated with chronic, non-communicable conditions. Under such conditions, the composition and direction of investment—rather than aggregate expenditure alone—becomes central for policy and management decision-making. Iranian studies have highlighted the importance of health expenditures as an economic-policy variable, including links to fiscal capacity (tax and oil revenues) and wider macroeconomic performance. Evidence at national and regional levels also indicates that government health expenditure can contribute to productivity and growth, but the strength and channels of this contribution can vary across provinces, reflecting differences in institutional capacity and infrastructure distribution. In addition, the management of health expenditures—how budgets are planned, targeted, and monitored—has been emphasized as a determinant of effectiveness within Iran's health insurance and service delivery arrangements. Together, these findings motivate a structured empirical evaluation of how healthcare infrastructure variables and public/private investment relate to core public health outcomes in Iran over time (Iravani Masoudi et al., 2018; Naderi & Khodabakhshi, 2019; Raeispour & Pajooyan, 2014; Raispour & Jamshid, 2014).

Recent empirical work further suggests that the health–economy relationship is not unidirectional. Health investments may stimulate growth through human capital accumulation, while economic and financial development can expand the resource base for health investment and enable technology adoption. For Iran specifically, evidence has been presented linking life expectancy improvements to broader financial development, health expenditures, and energy-related variables, underscoring the importance of macro-structural forces that shape health-system performance. Similarly, comparative studies in developing countries have re-evaluated the health expenditure–growth linkage in the context of global sanitary crises, noting that shocks can alter marginal effects and reveal structural vulnerabilities. These perspectives imply that the relationship between infrastructure, investment, and outcomes may evolve over time and may be subject to dynamic feedback and lagged adjustments—an empirical feature that motivates time-series structural modeling rather than static regression specifications (Elham & Mohammad, 2024; Gaies, 2022; Mohammad et al., 2024).

Another strand of the literature emphasizes that public health outcomes are shaped by environmental and contextual drivers that can indirectly affect health-system financing and demand. For instance, environmental pollution has been shown to increase public health expenditure through elevated disease burden and treatment demand, while broader governance and policy conditions can influence how societies respond to health-related risks. Although this study centers on infrastructure and investment, acknowledging these contextual determinants is important because they may affect the stability and responsiveness of expenditure and capacity variables over time. Moreover, shocks—whether environmental or economic—can interact with institutional performance and produce non-linear dynamics in health outcomes, further strengthening the rationale for modeling frameworks capable of capturing structural relationships, endogeneity, and dynamic interactions among system variables (Ghosh et al., 2018; Hao et al., 2018).

From a management standpoint, differentiating between public and private health investment is critical because the two sectors often follow distinct incentive structures, investment horizons, and accountability mechanisms. Public investment is typically driven by equity and universal access objectives, and it may prioritize underserved regions or preventive services with high social returns. Private investment, by contrast, may concentrate where demand is solvent and returns are higher, potentially accelerating capacity expansion and service quality but also risking uneven distribution if not guided by effective regulation. Empirical evidence in various contexts suggests that both sectors matter, but their relative effectiveness can differ depending on the broader institutional environment and the maturity of health markets. In parallel, the efficiency literature indicates that adding resources without strengthening managerial capability and system governance may generate diminishing returns. Hence, a comprehensive empirical assessment should jointly consider spending/investment, capacity variables, and human resources, while allowing for dynamic interdependence among them (Akinkugbe & Mamotlohi, 2020; Das & Guha, 2024; Mbau et al., 2023).

Beyond financing and infrastructure, workforce variables—physicians, nurses, and midwives—represent the operational core through which investments become services. Health systems with adequate physical infrastructure but insufficient staffing often experience bottlenecks, quality degradation, and access constraints. Conversely, improvements in staffing levels may have limited effects if facilities are under-equipped or geographically inaccessible. Therefore, in line with health policy goal-oriented analyses, several studies have incorporated health indicators and human resources to explain economic development and growth dynamics, including within regional and provincial assessments. Such work reinforces the need for integrated modeling strategies that treat infrastructure and human resources as complementary components of a single service-production system rather than independent determinants. This integrated view is consistent with managerial logic in service operations, where outcomes are produced through coordinated resource bundles rather than isolated inputs (Arefi et al., 2023; Marzieh et al., 2023; Ogundari & Awokuse, 2018).

In addition to classic health-system determinants, digital transformation has emerged as a new layer shaping how public systems coordinate, communicate, and deliver services. Studies on the digital economy and growth highlight that digitalization can reshape productivity and service accessibility, while research on digital governance suggests that information-based public programs can improve public well-being outcomes through better coordination and accountability. In the public health domain, policy communication and citizen engagement via social media have been shown to influence institutional trust and the effectiveness of public health messaging—an increasingly relevant factor for public compliance, service uptake, and crisis response. Although the primary mechanisms examined in this study relate to infrastructure and investment, digital governance and communication dynamics form a contextual backdrop that can amplify or dampen the effectiveness of investments by shaping coordination, transparency, and trust. From a management perspective, this underscores that "infrastructure" should be interpreted broadly as a socio-technical system, even if empirical measurement in a given study focuses on more conventional capacity indicators (Zhang et al., 2022; Zhang & Lu, 2025; Zou et al., 2025).

The Iranian development literature further reinforces the importance of linking health outcomes to broader measures of human development and regional disparities. Research applying fuzzy logic to estimate the Human Development Index across Iranian provinces and examining its relationship with economic growth indicates that development outcomes are spatially heterogeneous and that social-sector investments can be associated with growth performance. Complementary national work has explored causality between the Human Development Index and economic growth using regime-switching VAR approaches, suggesting that development–growth relationships can change across periods and may exhibit structural breaks. These findings are relevant to health infrastructure research because life expectancy is both a direct health outcome and a constituent of broader development indices; accordingly, understanding the determinants of life expectancy and mortality can also inform development policy and regional planning. This further supports the use of dynamic structural time-series methods capable of capturing evolving relationships rather than assuming fixed effects across decades (Afghah et al., 2019; Mehdiloo et al., 2016).

Another policy-relevant dimension concerns distributional consequences of health financing. Health expenditures can influence not only average health outcomes but also income distribution and equity, as health shocks and out-of-pocket payments are major drivers of poverty and vulnerability. Cross-national evidence among OIC members indicates that health expenditures may be linked to income inequality through multiple channels, including differential access to care and the fiscal incidence of health financing. Related development finance work on remittances and poverty, while not health-specific, highlights how income flows and financial resources affect welfare outcomes and can alter households' ability to cope with health costs. Together, these insights suggest that evaluating health investment is not merely a technical exercise in outcome maximization; it also has implications for equity, vulnerability, and inclusive development—key concerns in public sector management and national planning (Anyanwu & Andrew, 2019; Mohammad et al., 2024).

At the same time, global health events have underscored the systemic risks associated with infectious diseases and the importance of resilient health infrastructures. While the present study focuses on broad public health indicators rather than a specific disease, evidence on zoonotic and viral detection in animal reservoirs illustrates why infrastructure readiness, surveillance capacity, and service resilience remain central to health-system performance. Such studies contribute to the broader argument that capacity constraints can become binding under shocks, and that long-run investments in facilities, workforce, and financing architecture are foundational for system resilience. This perspective also supports adopting empirical designs that can capture how structural investments translate into outcomes over extended horizons, rather than only in short-run snapshots (Bittar et al., 2020; Gaies, 2022).

In summary, the literature converges on several points: (1) public health outcomes are shaped by a bundle of financial, infrastructural, and human-resource inputs; (2) the effectiveness of these inputs depends on managerial efficiency, institutional conditions, and dynamic feedback processes; and (3) in contexts such as Iran, long-run evaluation is essential due to structural shifts in disease burdens, fiscal conditions, and policy environments. Methodologically, these considerations motivate the use of dynamic structural time-series models that can accommodate endogeneity and lagged interdependence among variables—an approach increasingly used to investigate complex macro-sectoral relationships. Within this framework, life expectancy and mortality serve as core public health indicators that are both intrinsically important and analytically informative for understanding how health-system investments translate into societal welfare and development outcomes (Das & Guha, 2024; Meng, 2022; Yeshaw et al., 2025; Ying et al., 2022).

Accordingly, the aim of this study is to examine the long-run structural relationships between healthcare infrastructure (including hospital beds and health workforce) and public and private health-sector investment, and their effects on life expectancy and mortality rates in Iran.

2. Methods and Materials

The present study is applied in terms of purpose and is relevant to the national health sector, and in terms of nature it is descriptive–analytical, falling within the category of ex post facto research. The statistical sample of this study is Iran, and based on data availability, the study period covers 1986–2023. Data analysis was conducted using EViews software and the Structural Vector Autoregression (SVAR) model.

Following the studies by Das et al. (2024), Hu et al. (2018), Mbawu et al. (2023), and Yang et al. (2022), the following variables are used in the regression analysis: gross fixed capital formation (CAP), labor force participation rate (LF), population growth (POP), literacy rate (LR), hospital beds (HB), physicians (P), nurses and midwives (NM), total public sector investment in the health sector (GG), total private sector investment in the health sector (PH), life expectancy index (LE), and mortality rate (DR).

Life Expectancy Model

$$\begin{bmatrix} \varepsilon_{CAP} \\ \varepsilon_{LF} \\ \varepsilon_{POP} \\ \varepsilon_{LR} \\ \varepsilon_{HB} \\ \varepsilon_{P} \\ \varepsilon_{NM} \\ \varepsilon_{PH} \\ \varepsilon_{GG} \\ \varepsilon_{LE} \end{bmatrix} = \begin{bmatrix} a_{11}(1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21}(1) & a_{22}(1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{31}(1) & a_{32}(1) & a_{33}(1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{41}(1) & a_{42}(1) & a_{43}(1) & a_{44}(1) & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{51}(1) & a_{52}(1) & a_{53}(1) & a_{54}(1) & a_{55}(1) & 0 & 0 & 0 & 0 & 0 \\ a_{61}(1) & a_{62}(1) & a_{63}(1) & a_{64}(1) & a_{65}(1) & a_{66}(1) & 0 & 0 & 0 & 0 \\ a_{71}(1) & a_{72}(1) & a_{73}(1) & a_{74}(1) & a_{75}(1) & a_{76}(1) & a_{77}(1) & 0 & 0 & 0 \\ a_{81}(1) & a_{82}(1) & a_{83}(1) & a_{84}(1) & a_{85}(1) & a_{86}(1) & a_{87}(1) & a_{88}(1) & 0 & 0 \\ a_{91}(1) & a_{92}(1) & a_{93}(1) & a_{94}(1) & a_{95}(1) & a_{96}(1) & a_{97}(1) & a_{98}(1) & a_{99}(1) & 0 \\ a_{101}(1) & a_{102}(1) & a_{103}(1) & a_{104}(1) & a_{105}(1) & a_{106}(1) & a_{107}(1) & a_{108}(1) & a_{109}(1) & a_{1010}(1) \end{bmatrix} \times \begin{bmatrix} U_{CAP} \\ U_{LF} \\ U_{POP} \\ U_{LR} \\ U_{HB} \\ U_{P} \\ U_{NM} \\ U_{PH} \\ U_{GG} \\ U_{LE} \end{bmatrix}$$

Mortality Rate Model

$$\begin{bmatrix} \varepsilon_{CAP} \\ \varepsilon_{LF} \\ \varepsilon_{POP} \\ \varepsilon_{LR} \\ \varepsilon_{HB} \\ \varepsilon_{P} \\ \varepsilon_{NM} \\ \varepsilon_{PH} \\ \varepsilon_{GG} \\ \varepsilon_{DR} \end{bmatrix} = \begin{bmatrix} a_{11}(1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21}(1) & a_{22}(1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{31}(1) & a_{32}(1) & a_{33}(1) & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{41}(1) & a_{42}(1) & a_{43}(1) & a_{44}(1) & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{51}(1) & a_{52}(1) & a_{53}(1) & a_{54}(1) & a_{55}(1) & 0 & 0 & 0 & 0 & 0 \\ a_{61}(1) & a_{62}(1) & a_{63}(1) & a_{64}(1) & a_{65}(1) & a_{66}(1) & 0 & 0 & 0 & 0 \\ a_{71}(1) & a_{72}(1) & a_{73}(1) & a_{74}(1) & a_{75}(1) & a_{76}(1) & a_{77}(1) & 0 & 0 & 0 \\ a_{81}(1) & a_{82}(1) & a_{83}(1) & a_{84}(1) & a_{85}(1) & a_{86}(1) & a_{87}(1) & a_{88}(1) & 0 & 0 \\ a_{91}(1) & a_{92}(1) & a_{93}(1) & a_{94}(1) & a_{95}(1) & a_{96}(1) & a_{97}(1) & a_{98}(1) & a_{99}(1) & 0 \\ a_{101}(1) & a_{102}(1) & a_{103}(1) & a_{104}(1) & a_{105}(1) & a_{106}(1) & a_{107}(1) & a_{108}(1) & a_{109}(1) & a_{1010}(1) \end{bmatrix} \times \begin{bmatrix} U_{CAP} \\ U_{LF} \\ U_{POP} \\ U_{LR} \\ U_{HB} \\ U_{P} \\ U_{NM} \\ U_{PH} \\ U_{GG} \\ U_{DR} \end{bmatrix}$$

The left-hand side of the above equations represents the first-order logarithmic differences of the dependent variables. On the right-hand side, the matrix A(L) is a square matrix containing polynomials in terms of the lag operator. For example, the element in the i-th row and j-th column of the matrix A(L), denoted as a_ij(L), represents the response of the i-th variable to the j-th structural variable. The vector E = [U_ij] contains the structural disturbance terms.

3. Findings and Results

Initially, to ensure the absence of spurious regression, unit root and cointegration tests are employed. In this study, the commonly used Phillips–Perron test is applied (Table 1).

Table 1

Results of the Phillips–Perron (PP) Test at the Level of Model Variables

Variable Status	Probability	Statistic	Variables
---	0.4740	-0.5452	CAP
I(1)	0.0000	-8.8967	D(CAP)
---	0.5531	-0.3472	DR
I(1)	0.0000	-6.5483	D(DR)

---	0.5545	-0.3434	GG
I(1)	0.0000	-8.2947	D(GG)
---	0.1641	-1.3389	HB
I(1)	0.0000	-7.3635	D(HB)
---	0.1143	-3.1310	LE
I(1)	0.0000	-7.1371	D(LE)
---	0.5547	-0.3429	LF
I(1)	0.0000	-68.5995	D(LF)
---	0.1963	-1.2314	LR
I(1)	0.0000	-4.7081	D(LR)
---	0.6810	0.01447	NM
I(1)	0.0000	-8.8732	D(NM)
---	0.1861	-1.2639	PH
I(1)	0.0000	-15.2172	D(PH)
---	0.5981	-0.2258	POP
I(1)	0.0000	-4.8949	D(POP)

Based on the theoretical foundations of stationarity tests, the null hypothesis (H_0) in these tests assumes non-stationarity of the variables. Considering the test results, it can be concluded that all variables in the model are stationary at the first difference level, I(1).

Since the variables of the model are integrated of the same order, I(1), cointegration tests are employed to identify the existence of a long-run equilibrium relationship among the model variables. For this purpose, the Johansen–Juselius method is used. Implementing this test requires determining the number of cointegrating vectors. To examine the results of the cointegration test, an appropriate specification must be selected with respect to the presence or absence of a time trend and an intercept in the cointegrating vector. In this regard, five specifications are considered: the first model includes neither an intercept nor a time trend; the second model includes a restricted intercept and no time trend; the third model includes an unrestricted intercept and no time trend; the fourth model includes an unrestricted intercept and a restricted time trend; and the fifth model includes both an unrestricted intercept and an unrestricted time trend. These five models are estimated for the variables, ranging from the most restricted specification (Model 1) to the least restricted specification (Model 5). Subsequently, the null hypothesis of no cointegrating vector is tested against the alternative hypothesis of one cointegrating vector, followed by testing the hypothesis of at most one cointegrating vector against two cointegrating vectors. This procedure continues until the existence of up to $n - 1$cointegrating vectors (where $n$is the number of variables) is examined. A summary of the results of the Trace test (λ_{Trace}) and the Maximum Eigenvalue test (λ_{Max}) regarding the number of cointegrating vectors based on the five specifications is reported in Tables 2 and 3. As can be observed, the null hypothesis of no cointegrating vector against the existence of one cointegrating vector among the variables is rejected; therefore, at least one cointegrating vector exists among the variables under study (Tables 4 and 5).

Table 2

Summary of the Results for the Number of Cointegrating Vectors in the Life Expectancy Index Model

Model	Model 1	Model 2	Model 3	Model 4	Model 5
Trace Test	4	6	6	3	4
Maximum Eigenvalue Test	3	5	2	5	6

Table 3

Summary of the Results for the Number of Cointegrating Vectors in the Mortality Rate Model

Model	Model 1	Model 2	Model 3	Model 4	Model 5
Trace Test	7	4	5	5	3
Maximum Eigenvalue Test	6	5	3	3	6

Table 4

Results of the Cointegration Test for the Mortality Rate Model

Maximum Eigenvalue Test Statistic	Critical Value at 95%	Probability	Trace Statistic	Critical Value at 95%	Probability	H1 Hypothesis	H0 Hypothesis
133.9674	64.5047	0.0000	425.9275	239.2354	0.0000	r = 1	r = 0
98.3880	58.4335	0.0000	291.9600	197.3709	0.0000	r = 2	r ≤ 1
50.8708	52.3626	0.0705	193.5720	159.5297	0.0002	r = 3	r ≤ 2
37.1217	46.2314	0.3337	142.7011	125.6154	0.0030	r = 4	r ≤ 3
33.3606	40.07757	0.2343	105.5794	95.7536	0.0089	r = 5	r ≤ 4
30.2211	33.8768	0.1285	72.2187	69.8188	0.0318	r = 6	r ≤ 5
22.6415	27.5843	0.1893	41.9975	47.8561	0.1588	r = 7	r ≤ 6
8.8351	21.1316	0.8455	19.3560	29.7970	0.4675	r = 8	r ≤ 7
7.3527	14.2646	0.4483	10.5208	15.4947	0.2428	r = 9	r ≤ 8
3.1680	3.8414	0.0751	3.1680	3.8414	0.0751	r = 10	r ≤ 9

Table 5

Results of the Cointegration Test for the Life Expectancy Index Model

Maximum Eigenvalue	Critical Value at 95%	Probability	Trace Statistic	Critical Value at 95%	Probability	H1 Hypothesis	H0 Hypothesis
101.5913	64.5047	0.0000	358.3717	239.2354	0.0000	r = 1	r = 0
60.1766	58.4335	0.0333	256.7804	197.3709	0.0000	r = 2	r ≤ 1
55.5628	52.3626	0.0227	196.6038	159.5297	0.0001	r = 3	r ≤ 2
39.7751	46.2314	0.2082	141.0409	125.6154	0.0041	r = 4	r ≤ 3
33.7474	40.0775	0.2169	101.2658	95.7536	0.0198	r = 5	r ≤ 4
26.2673	33.8768	0.3047	67.5183	69.8188	0.0753	r = 6	r ≤ 5
18.8912	27.5843	0.4230	41.2509	47.8561	0.1808	r = 7	r ≤ 6
10.0967	21.1316	0.7355	22.3597	29.7970	0.2789	r = 8	r ≤ 7
7.2350	14.2646	0.4617	12.2630	15.4947	0.1448	r = 9	r ≤ 8
5.0279	3.8414	0.0249	5.0279	3.84146	0.0249	r = 10	r ≤ 9

After establishing the stationarity of the model variables, the first issue in vector autoregression models is determining the optimal lag length. In this study, the Schwarz–Bayesian Criterion (SC), Akaike Information Criterion (AIC), Final Prediction Error (FPE), Hannan–Quinn Criterion (HQ), and the Likelihood Ratio (LR) test are used to determine the lag length. Because the Schwarz–Bayesian criterion follows the parsimony principle and assigns the greatest importance to reducing parameters or simplifying the system (as opposed to achieving a better fit), it is more appropriate for small samples, particularly the selected sample size in this study. Therefore, lag 1 is selected as the optimal lag for both the life expectancy index model and the mortality rate model (Tables 6 and 7).

Table 6

Determination of the Optimal Lag in the Life Expectancy Index Model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	137.1031	NA	4.06e−16	−7.0612	−6.6214	−6.9077
1	293.0173	216.5475*	2.22e−17*	−10.1676	−7.3290*	−8.4788*
2	409.4697	97.04367	3.92e−17	−11.0816*	−1.8444	−7.8576

*Indicates the optimal lag.

Table 7

Determination of the Optimal Lag in the Mortality Rate Model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	34.01834	NA	1.25e−13	−1.3343	−0.8944	−1.1808
1	200.0410	230.5870*	3.89e−15	−5.0022*	−2.1637*	−5.3123*
2	347.2861	122.7043	1.24e−15*	−4.6270	1.6101	−4.4029

*Indicates the optimal lag.

To ensure that the regression is not spurious or artificial, a unit root test was also performed for the entire regression model. If the SVAR model is unstable, the results obtained are not reliable. To examine the stability of the estimated model, the AR graph is used. This graph shows the inverse roots of the characteristic polynomial of an AR process. If the absolute values of all these roots are less than one and lie inside the unit circle, the estimated SVAR model is stable. The AR graphs in Figures (1) and (2) indicate that the inverse of all characteristic roots lies within the unit circle, and the estimated SVAR models satisfy the stability condition.

Figure 1

Unit Circle (Inverse Roots) Test for the Life Expectancy Index Model

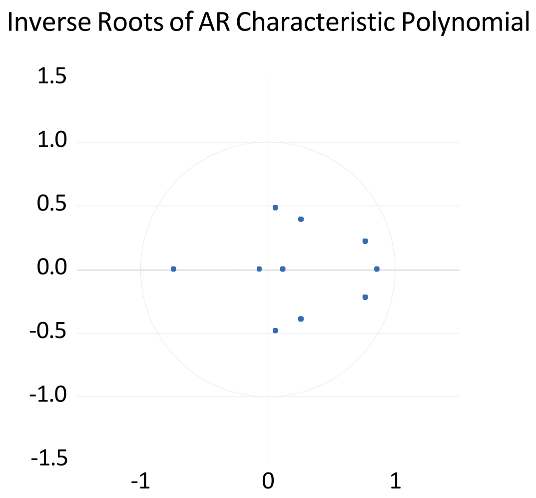
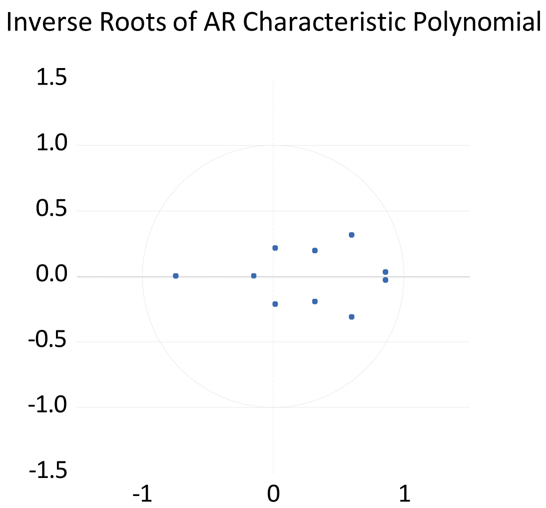


Figure 2

Unit Circle (Inverse Roots) Test for the Mortality Rate Model



The SVAR results aimed at examining the response of public health indicators (life expectancy and mortality rate) to healthcare infrastructure are reported in Table 8. This table presents the system of equations linking structural shocks and reduced-form shocks.

Table 8

Estimated Long-Run Equilibrium Relationship for the Study Models

Variables	Life Expectancy Index Model		Mortality Rate Model	
	Coefficient	p-value	Coefficient	p-value
Impulse coefficient of gross fixed capital formation	0.2657	0.0428	−0.2852	0.0401
Impulse coefficient of labor force	0.1568	0.1052	0.1956	0.0719
Impulse coefficient of population	0.1144	0.1563	0.2972	0.1935
Impulse coefficient of literacy rate	0.2984	0.0856	−0.3637	0.2581
Impulse coefficient of hospital beds	0.4640	0.0256	0.9852	0.0351
Impulse coefficient of physicians	0.3250	0.0109	−0.8824	0.0332
Impulse coefficient of nurses and midwives	0.2365	0.0185	−0.7000	0.0228
Impulse coefficient of total public sector investment in health	0.2298	0.0029	−0.2640	0.0051
Impulse coefficient of total private sector investment in health	0.3482	0.0001	−0.1067	0.0011

The estimated SVAR results indicate that the coefficients of the key variables and the interacting impulses in the matrix equations are statistically meaningful and consistent with Iran's economic conditions. The main variables that are necessary and analytically relevant in the SVAR results are as follows: impulses originating from gross fixed capital formation, labor force, population, literacy rate, hospital beds, physicians, nurses and midwives, total public investment in the health sector, and total private investment in the health sector increase and improve the life expectancy index. A notable point in this model is the stronger and comparatively more statistically meaningful effect of private sector investment, followed by public sector investment in the health sector. The population, labor force, and literacy rate variables do not have statistically significant effects on the life expectancy index at the 95% confidence level; however, the number of nurses and midwives, physicians, hospital beds, and gross fixed capital formation have statistically significant effects on life expectancy at the 95% confidence level.

With respect to the mortality rate model, it can be stated that impulses originating from hospital beds, physicians, nurses and midwives, total public investment in the health sector, and total private investment in the health sector reduce the mortality rate index in the country. Regarding population, literacy rate, and labor force, their effects on mortality in Iran are not statistically significant at the 95% confidence level. In contrast, the number of nurses and midwives, physicians, and gross fixed capital formation have statistically significant effects on the mortality rate index at the 95% confidence level. Consistent with the life expectancy model, the estimation results indicate that the most statistically meaningful effect on mortality is associated with private sector investment, followed by public sector investment in the health sector.

Variance decomposition makes it possible to examine the extent to which changes in a time series are driven by its own innovations and the extent to which they are influenced by the disturbance components of other endogenous variables within the system. Variance decomposition separates the changes in an endogenous variable attributable to shocks in other endogenous variables. In this approach, the contribution of shocks to different variables is allocated across the forecast error variance of a given variable in response to the shocks introduced into the model variables. Accordingly, the contribution of each variable to the changes in other variables can be measured over time. In fact, variance decomposition reveals the share of each shock in predicting a specific variable. Tables 9 and 10 report the variance decomposition for the life expectancy index and mortality rate variables. Variance decompositions are defined such that, in the first period (short run), fluctuations in each variable are typically explained by its own shocks; however, over longer time horizons, the contribution of other variables to predicting the behavior of a given variable increases depending on their importance.

In this section, based on the estimated model, variance decomposition of the model variables is performed, and the results are reported for each model. In these tables, the S.E. column indicates the forecast error of the relevant variables across different periods. Because this error is calculated each year based on the prior year's error and its sources are changes in current values and future impulses, it increases over time. The results of the tables indicate that, in both the mortality rate and life expectancy index models, the greatest explanatory contribution is associated with private sector investment in health, which corroborates the earlier parts of the model indicating that this variable exhibits the most statistically meaningful effect.

Table 9

Variance Decomposition for the Life Expectancy Index Model

Period	S.E.	LE	LF	POP	LR	HB	P	NM	PH	GG	CAP
1	0.0800	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.0978	82.5649	0.3705	0.4644	1.8669	1.3797	1.0073	0.3031	9.6583	2.3833	0.0012
3	0.1002	79.0571	0.3616	0.4444	4.0324	1.4210	1.0583	0.3150	9.2740	2.4689	1.5666
4	0.1074	68.9549	0.5015	0.9549	3.6681	1.2479	1.3904	1.8933	8.8469	5.8996	6.6420
5	0.1128	63.5854	0.4583	1.5158	3.4527	1.1605	1.2807	3.1400	9.0696	8.78576	7.5509
6	0.1149	62.3003	0.4506	1.6970	3.4860	1.2873	1.2473	3.4774	9.1426	9.2827	7.6282
7	0.1164	60.9159	0.4533	1.7888	3.8451	1.3119	1.2205	3.8211	9.7013	9.1188	7.8229
8	0.1182	59.2958	0.5023	1.8628	3.9594	1.2929	1.2913	4.1247	10.5840	8.9456	8.1403
9	0.1197	58.5645	0.6677	1.8194	3.8779	1.3166	1.2917	4.2411	10.9520	8.7595	8.5083
10	0.1207	58.2349	0.9560	1.8023	3.8210	1.3171	1.2726	4.2750	11.0090	8.6302	8.6807

Table 10

Variance Decomposition for the Mortality Rate Model

Period	S.E.	DR	CAP	LF	POP	LR	HB	P	NM	PH	GG
1	0.6528	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.8852	79.2763	0.6883	2.5690	0.2359	0.2798	9.2902	7.1741	0.0000	0.0156	0.4704
3	1.0753	69.8017	0.5643	1.9973	0.2472	2.2916	7.3726	9.6379	0.2576	2.6393	5.1901
4	1.2630	71.4665	0.4143	1.8588	0.4601	2.1562	5.3933	7.5984	0.6358	5.7381	4.2780
5	1.3545	68.5373	1.0315	1.6898	0.5176	2.8686	4.7911	6.6192	0.7812	7.9923	5.1710
6	1.4343	64.2718	0.9682	1.8297	0.4759	5.7468	4.8804	7.2418	0.9291	7.3067	6.3491
7	1.4873	60.8409	0.9006	2.2003	0.4882	6.7712	5.5104	9.0213	0.8902	6.9775	6.3989
8	1.5541	56.4193	2.0061	2.4877	0.4906	6.9736	5.6390	10.6170	0.8523	8.1050	6.4084
9	1.6342	51.6996	4.3076	2.4597	0.5706	6.3770	5.3637	10.4030	0.8745	11.9560	5.9864
10	1.7308	46.1950	8.4548	2.3335	0.6590	5.8504	4.7827	9.5961	0.9149	15.5630	5.6498

4. Discussion and Conclusion

The results of this study provide robust empirical evidence on the structural relationships between healthcare infrastructure, public and private health-sector investment, and key public health outcomes in Iran. The SVAR estimations indicate that investments in healthcare infrastructure and human resources exert statistically significant and economically meaningful effects on life expectancy and mortality rates over the long run. In particular, the positive response of life expectancy to shocks in hospital beds, physicians, nurses and midwives, and gross fixed capital formation confirms the central premise of the health capital framework, which conceptualizes health as a productive asset that can be augmented through sustained investment in both physical and human inputs (Grossman, 2017). These findings are consistent with the view that healthcare infrastructure is not merely a supportive background factor but a core driver of population health and, by extension, socioeconomic development (Arefi et al., 2023; Marzieh et al., 2023).

A salient result of the analysis is the comparatively stronger and more statistically significant effect of private sector investment relative to public sector investment on both life expectancy improvements and mortality reduction. This pattern suggests that private investment may be more efficient in translating financial resources into service capacity and outcomes, possibly due to stronger managerial incentives, faster capital deployment, or greater flexibility in resource allocation. Similar conclusions have been reported in empirical investigations from other developing and emerging economies, where private participation in healthcare has been associated with improved service availability and responsiveness when operating within an enabling regulatory framework (Akinkugbe & Mamotlohi, 2020; Das & Guha, 2024). At the same time, the significant—though comparatively smaller—impact of public health investment underscores the continued importance of government spending in ensuring baseline access, equity, and system-wide stability, particularly in contexts characterized by regional disparities and uneven income distribution (Baker et al., 2019; Raeispour & Pajooyan, 2014; Raispour & Jamshid, 2014).

The statistically significant role of hospital beds and healthcare personnel highlights the importance of capacity and workforce availability as binding constraints in the Iranian health system. The findings suggest that increases in infrastructure and staffing levels directly improve life expectancy while simultaneously reducing mortality, reinforcing evidence from both national and international studies that emphasize the complementary relationship between physical capacity and human resources (Mbau et al., 2023; Ogundari & Awokuse, 2018). This result aligns with provincial-level analyses in Iran that show health indicators and service capacity as key contributors to development outcomes (Marzieh et al., 2023; Mehdiloo et al., 2016). It also resonates with broader health-system efficiency literature, which argues that without adequate staffing and facility readiness, additional spending yields diminishing marginal returns (Mbau et al., 2023).

In contrast, variables such as population growth, labor force participation, and literacy rate did not exhibit statistically significant effects on life expectancy and mortality at the 95% confidence level in the estimated models. This finding does not necessarily imply that these factors are unimportant for health outcomes, but rather suggests that their effects may be indirect, mediated through income, institutional quality, or health-system capacity rather than operating as direct drivers within the structural framework considered here. Previous studies have shown that education and demographic factors often influence health through complex pathways involving income growth, behavioral change, and access to services, which may not be fully captured in aggregate time-series models (Afghah et al., 2019; Anyanwu & Andrew, 2019). Moreover, the lack of short- to medium-term statistical significance may reflect lag structures or threshold effects, where improvements in education and labor-market conditions translate into health gains only after prolonged periods or in conjunction with infrastructure expansion (Meng, 2022; Ying et al., 2022).

The mortality rate model further reinforces the centrality of healthcare capacity and investment structure. The negative and statistically significant responses of mortality to shocks in hospital beds, physicians, nurses and midwives, and both public and private health investment indicate that these factors are critical in reducing preventable deaths. These results are consistent with cross-country evidence showing that health expenditure and infrastructure development can reduce mortality, particularly in low- and middle-income settings where baseline capacity constraints are more pronounced (Akinkugbe & Mamotlohi, 2020; Gaies, 2022). The stronger effect of private investment on mortality reduction mirrors findings in the life expectancy model and suggests that private sector engagement may play a crucial role in expanding access to timely and effective care, especially for acute and chronic conditions requiring specialized services (Das & Guha, 2024).

Variance decomposition analysis provides additional insight into the dynamic importance of different shocks over time. The results indicate that, although short-run fluctuations in life expectancy and mortality are largely explained by their own innovations, the explanatory power of private health investment increases substantially over longer horizons. This pattern confirms that private investment is not only statistically significant in the structural equations but also a dominant contributor to forecast variance in public health outcomes. Similar dynamic patterns have been observed in studies examining the long-run effects of health expenditure and investment on growth and development, where private and mixed financing arrangements often show stronger persistence and long-term influence (Gaies, 2022; Meng, 2022). These findings support the argument that policy evaluations based solely on contemporaneous correlations may underestimate the true impact of health investments that operate through gradual capacity accumulation and system learning.

The results also align with Iranian studies emphasizing the role of fiscal structure and revenue sources in shaping health expenditure effectiveness. Research on the determinants of health spending in Iran has shown that reliance on oil revenues and tax capacity can influence the stability and sustainability of public health investment, potentially affecting its long-run impact (Naderi & Khodabakhshi, 2019). In this context, the relatively stronger performance of private investment may reflect its insulation from fiscal volatility and budgetary constraints, enabling more consistent capital formation in the health sector. This interpretation is consistent with findings linking financial development and health expenditure to life expectancy improvements in Iran, which suggest that diversified financing channels can enhance system resilience and performance (Elham & Mohammad, 2024; Mohammad et al., 2024).

From a broader policy and management perspective, the findings underscore the importance of efficiency, governance, and institutional design in determining how health investments translate into outcomes. Evidence from efficiency-oriented reviews highlights that health systems with similar expenditure levels can produce markedly different outcomes depending on managerial practices and governance quality (Mbau et al., 2023). In parallel, emerging research on digital governance and policy communication suggests that coordination, transparency, and institutional trust can amplify the effectiveness of public programs, including health investments (Zhang & Lu, 2025; Zou et al., 2025). Although digital variables are not explicitly modeled in this study, they form part of the broader institutional environment that shapes investment effectiveness and may partially explain why private sector investments, often accompanied by more flexible management structures, demonstrate stronger impacts.

The study's findings also resonate with the literature linking health outcomes to broader development and inequality considerations. Improvements in life expectancy and reductions in mortality contribute directly to human development and indirectly to productivity and income growth, reinforcing virtuous cycles of development (Grossman, 2017; Ogundari & Awokuse, 2018). Conversely, inadequate health investment can exacerbate inequality and vulnerability, as health shocks remain a major driver of poverty and income disparity. Cross-national evidence among OIC countries suggests that health expenditures can influence income inequality, underscoring the distributional implications of health financing strategies (Mohammad et al., 2024). The present results therefore highlight that investment decisions in the health sector are not only technical efficiency issues but also central to inclusive and sustainable development strategies.

Overall, the discussion of results suggests that Iran's public health outcomes are strongly shaped by the structure and composition of healthcare investment and infrastructure. The dominance of private investment effects does not diminish the role of public spending but rather points to the need for complementary and coordinated strategies that leverage the strengths of both sectors. These findings support a management-oriented perspective in which healthcare infrastructure development, human resource expansion, and diversified financing are jointly optimized to achieve long-term improvements in population health and system sustainability (Das & Guha, 2024; Yeshaw et al., 2025).

Despite the robustness of the empirical approach, this study has several limitations. First, the analysis relies on aggregate national-level time-series data, which may mask important regional disparities in healthcare infrastructure and outcomes within Iran. Second, although the SVAR framework captures dynamic and structural relationships, it cannot fully account for all institutional, behavioral, and policy factors that may influence health outcomes. Third, data constraints limit the inclusion of qualitative dimensions of healthcare quality, governance, and service effectiveness, which may also play a critical role in shaping life expectancy and mortality trends.

Future studies could extend this line of inquiry by employing regional or provincial panel data to explore spatial heterogeneity in the effects of healthcare infrastructure and investment. Incorporating indicators of service quality, governance, and digital health capacity may provide a more nuanced understanding of how investments translate into outcomes. In addition, future research could examine potential nonlinearities and threshold effects, as well as interactions between health investment and broader macroeconomic or environmental variables, to better capture the complexity of health-system dynamics.

From a practical standpoint, policymakers and health-sector managers should prioritize coordinated investment strategies that balance public and private participation while strengthening regulatory and managerial capacity. Emphasis should be placed on expanding critical infrastructure and human resources in underserved areas, improving efficiency in resource allocation, and fostering an institutional environment that encourages responsible private investment. Such an integrated approach can enhance the long-term effectiveness and sustainability of the health system and contribute to improved public health outcomes.

Authors' Contributions

Authors contributed equally to this article.

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In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

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