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Evolution and interaction mechanisms of China's high-performing national healthcare system

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Abstract

Objectives This study aims to identify the dimensions and evolutionary pathways of China's high-performing national healthcare system, as well as the interaction mechanisms between the digital and traditional healthcare dimensions.

Methods This study first constructs a high-performing healthcare evaluation index comprising four dimensions: digital healthcare, healthcare resource allocation, healthcare output, and healthcare effectiveness. It next presents a multilevel structural dynamic factor model to examine the evolutionary pathway of China's national healthcare system. It then analyses the interaction mechanism of each healthcare dimension based on the impulse response function.

Results First, the upward trend in the overall performance of China's high-performing national healthcare system demonstrates that it is significantly improving. Second, the overall performance of China's high-performing national healthcare system has been most impacted by healthcare effectiveness and least impacted by healthcare output. The performance is trending upward for digital healthcare and healthcare resource allocation but downward for healthcare output and effectiveness. Third, increasing healthcare resource allocation and output promotes digital healthcare. The improvement in digital healthcare performance significantly and positively impacts healthcare effectiveness, while having weaker effects on healthcare resource allocation and healthcare output.

Conclusions The performance of China's high-performing national healthcare system is improving. However, healthcare resource allocation and health outcomes require further optimisation, and the integration capacity of traditional healthcare with digital healthcare must be strengthened.

Keywords High-performing healthcare, Indicator system, Multilevel structural dynamic factor model, Evolution, Interaction mechanism

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Introduction

Providing high-performing healthcare is challenging worldwide, particularly as a paradigm shift in the prevalence of predominantly chronic and non-communicable diseases is projected to significantly increase healthcare costs across countries [1]. Indeed, poor healthcare quality is a serious impediment to reducing mortality [2]. Therefore, reforming healthcare has become a key focus of policymakers in various countries. A healthcare system is defined as high-performing if it can effectively respond to the evolving demands for medical services and deliver improved and trustworthy medical services [2]. High-performing healthcare is characterised by its systemic nature, meaning that its realisation is jointly impacted by its medical services' objectives, structure, processes, and outcomes [3]. As Daniels noted [4], healthcare services not only have economic attributes related to profit-seeking and competitiveness but also have social attributes focusing on fairness and social welfare. Healthcare system reforms must find a more reasonable balance between its economic and social attributes to achieve the profit goals of healthcare providers and the fair distribution of healthcare services [5, 6]. However, the definition of high-performing healthcare remains unclear [7], which prevents not only the development of clear norms for practice but also the ability to generalise research findings across countries.

The definitions and measures of 'high-performing healthcare' vary considerably across studies, possibly due to the market nature of healthcare systems. While Kruk et al. [2] stated that a high-performing healthcare system should provide sustainable, equitable, trustworthy, and efficient healthcare, the healthcare market is known to possess greater uncertainty in quality than other commodities [8]. Moreover, the plurality of definitions for 'high-performing healthcare' partly stems from differences in measurement subjects, such as hospitals [9, 10], primary care facilities [11], and national healthcare systems [12]; this study focuses on national healthcare systems. Finally, overall healthcare performance can generally be divided into input, process, and output qualities [13]. Studies such as Ahluwalia et al. [7] have defined the concept of interest mainly based on the multidimensional performance of healthcare services (e.g. quality of care, cost, and accessibility).

Notably, as information technology continues to improve, digital technology will holistically impact the healthcare system's service delivery processes and performance [14]. Digital technologies and data have become fundamental inputs for healthcare, with electronic medical records, health information systems, and various types of sensors widely used [15]. Therefore, integrating digital technologies with healthcare services has become inevitable [16], and digital technologies will change the division of labour in healthcare [17], service delivery, and healthcare performance [18]. Given this context, a natural question is how digital healthcare will affect traditional healthcare delivery and, in turn, overall healthcare system performance. However, few studies have incorporated digital healthcare into frameworks assessing healthcare performance [19].

Among all systems, those in healthcare are some of the most complex [20]. In these systems, any unidimensional change will not drive it to improve in performance. Therefore, healthcare system reforms emphasise efforts to influence the organisation and delivery of healthcare services via system-level changes [21]. Due to this complexity, particularly the non-linear interactions of micro-agents in complex systems [22], healthcare performance assessment must encompass the healthcare system's multidimensional performance. That is, dynamic changes in the relationships of interest between the healthcare system's constituent agents will affect each agent's behaviour and strategies, often leading to discrepancies between the practice and policy expectations of high-performing healthcare. Therefore, research must clarify the definition and extension of high-performing healthcare and explore the interaction mechanisms of its internal components from a system perspective to help policymakers realise high-performing healthcare.

Therefore, we construct a high-performing healthcare evaluation index to examine the evolutionary pathway and internal interactions of China's national healthcare system. Since 2009, China has implemented healthcare reforms to provide higher-performing healthcare services, but its outcomes have not met policy expectations [23]. After 2015, China's healthcare market began promoting the use of electronic medical records and health information systems, which are proposed as potential mechanisms to facilitate the development of a high-performing healthcare system. Therefore, we first constructed a healthcare high-performing evaluation index, including traditional and digital healthcare services in its framework. Then, we employed a multilevel structural dynamic factor model to capture the evolutionary pathway of a high-performing national healthcare system and its dimensions in China. Finally, we used the impulse response function to explore the interaction mechanisms of the dimensions within China's national healthcare system.

This study offers three main contributions that address gaps in the literature. Firstly, most previous studies have measured high-performing healthcare through the dimensions of healthcare quality, cost, and accessibility [7] while overlooking the impact of digital healthcare. Therefore, we constructed a high-performing evaluation index incorporating digital and traditional healthcare services in its evaluation framework. This index can more comprehensively capture the characteristics of high-performing healthcare. Secondly, healthcare systems are complex and evolve dynamically, and static research offers only a limited perspective on their performance. To address this limitation, we use a multilevel structural dynamic factor model to examine the dynamic evolution of China's national healthcare system from 2017 to 2023. Thus, we explore the evolutionary pathway of China's national healthcare system, allowing us to ascertain its systematic and localised development trends and provide evidence for policy and management to support high-performing healthcare. Finally, the interactions of the participating agents within the healthcare system lead to deviations from the practices and expectations of a high-performing healthcare system. Therefore, we used impulse response functions to examine the interaction mechanisms of the dimensions of China's national healthcare system to identify the currently most and least important dimensions and discuss whether digital and traditional healthcare services can synergistically contribute to realising high-performing healthcare. This study deepens systems thinking in healthcare research and, in turn, refines our understanding of high-performing healthcare.

Theoretical model construction

High-performing healthcare

High-performing healthcare systems can be measured at three levels: inputs, processes, and outcomes. The Committee on Quality of Health Care in America [24] described six domains of high-performing healthcare: safe, effective, equitable, patient-centered, timely, and efficient. Kruk et al. [2] further defined this concept as healthcare that can respond to changes in healthcare needs with continual improvement while remaining trustworthy. Ahluwalia et al. [7] found that while a consistent definition of high-performing healthcare is lacking, existing studies have mainly focused on healthcare quality, cost, and accessibility as dimensions. Finally, while healthcare systems can be examined at multiple levels, this study examines China's healthcare system at the national level.

A national-level healthcare system is complex, as its performance depends on the evolution and interactions of its subsystems [25]. As non-linear interactions occur between micro-agents in complex systems [23], different characteristics will emerge at the macro level as micro-agents adjust their operational strategies according to the needs of their interests [26]. For example, while China launched its healthcare reform in 2009 to improve the quality of the healthcare system by integrating healthcare services, hospitals often refuse to refer patients to other healthcare organisations to maximise their profit [11]. This practice will manifest at the macro level as a deviation between the practical outcomes of healthcare system reforms and policy expectations [12]. Therefore, to capture the meaning of high-performing healthcare in detail, we must develop and employ a definition that includes multiple dimensions of healthcare service performance. Consequently, we constructed an index for evaluating high-performing healthcare, as detailed in the following section.

Construction of a high-performing healthcare evaluation index

A high-performing healthcare evaluation index for China must be constructed based on the current objectives of China's healthcare reform. According to the Donabedian model, healthcare performance reflects the values and goals of the current healthcare system and society; therefore, it is defined pluralistically and dynamically [27]. In China, the distribution of healthcare resources has long been imbalanced due to the uneven allocation of medical resources and social development [28], which has exacerbated the conflict between healthcare accessibility and affordability, making it one of the foremost medical contradictions in Chinese society [28, 29]. To improve the quality and efficiency of healthcare, China has adopted the integration of healthcare resources as a core measure in its healthcare reform. With the development of digital technologies, the Chinese government has introduced policies such as the '14 th Five-Year Plan for National Health Informatization' to promote the sharing of medical data and the integration of resources and to encourage the use of digital technologies to empower healthcare reform [30].

Notably, the digital transformation of the healthcare field is proceeding at an unprecedented pace [31]. Electronic health records, blockchain, and the Internet of Things have been widely applied [32]. Electronic health records store patient information digitally, facilitating information sharing among healthcare institutions, insurance companies, and patients, thereby enhancing the continuity of medical services [33]. In addition, artificial intelligence can analyse patients' clinical data to provide personalised treatment recommendations, laying the foundation for implementing precision medicine [34]. The combination of artificial intelligence and robotics, especially in telemedicine, has improved the equitable distribution of medical resources [35]. Digital technologies not only enhance the cost-effectiveness of medical services but also change the structure of the healthcare system [36, 37]. However, while digital technologies provide patients with more personalised and timely medical services, they also bring new challenges to academic research and industry practice [38]. Therefore, how to assess the scale and characteristics of digital healthcare and how digital healthcare will impact traditional medical services have become urgent research questions [19].

Since digital healthcare has become integral to healthcare services, we have incorporated digital and traditional healthcare services into our evaluation framework. Based on existing research, we define high-performing healthcare systems as those evolving dynamically and capable of delivering timely, effective, and efficient healthcare services. As shown in Table 1, the Donabedian model divides healthcare performance into three dimensions (structure, process, and outcome), with efficiency significantly influencing the performance of all three [27]. Braithwaite et al. [39] conducted a comparative analysis of healthcare performance measurement frameworks in countries such as the United States, Australia, and Canada, and found that although these frameworks generally cover core dimensions such as healthcare capacity, effectiveness, quality, and efficiency, there are significant differences in the selection of specific indicators. Combining the Donabedian model with the objectives of China's healthcare reform, this study's high-performing healthcare evaluation index comprises three dimensions: healthcare resource allocation, healthcare output, and healthcare effectiveness. Since digital healthcare functions as a healthcare resource input and directly affects the process and outcome of healthcare services, we measured it as a separate dimension.

Digital healthcare

Digital healthcare emphasises using information and big data technologies to deliver high-performing healthcare services [40]. It manifests in various forms, including medical decision support [34], telemedicine [41], and internet-based healthcare [42]. As both a healthcare resource and an integral part of healthcare services, digital healthcare assumes the dual roles of structure and process within this study's framework. China's '14 th Five-Year Plan for National Health Informatization' advocates for advancing 'Internet + Healthcare' in large general hospitals, with expanding digital healthcare forming the foundation for its implementation [30]. Therefore, this study selected indicators such as the scale of internet medical users, online pharmaceutical retail sales, and the online consultation market to assess the development status of digital healthcare in China across two dimensions: (i) user scale and activity and (ii) market scale.

Table 1 The dimensions of the Donabedian model

Dimension	Description
Healthcare outcome	Using healthcare outcomes (e.g. recovery, function, and survival) as quality indicators.
Healthcare process	Assessing the healthcare process directly, including the appropriateness of information, the rationality of diagnosis and treatment, and technical competence.
Structural assessment	Studying the environment and tools in which care occurs, such as facilities, equipment, and personnel qualifications.
Efficiency	Includes both logical and economic efficiency.

Healthcare resource allocation

Healthcare resource allocation refers to distributing resources to improve population health and maximise welfare [43]. It measures healthcare structure and typically includes information, physical, and financial resources [44]. Therefore, this study sets the secondary indicators for the healthcare resource allocation dimension as healthcare resources and facilities, medical expenditures, and insurance coverage, corresponding to the structural assessment in the Donabedian model. This study selected the tertiary indicators for the healthcare resource allocation dimension based on Feng et al. [12], who used the number of beds and equipment stock as indicators of healthcare resource input, and The Commonwealth Fund [45], which used insurance coverage and medical expenditures as indicators of the healthcare system.

Healthcare output

Healthcare output measures healthcare outcomes, including the health status of the population and the economic burden of service provision [2]. Among the indicators of health outcomes, mortality rate is the most widely used quality indicator [46, 47]. However, the number of deaths in the population is relatively small, making it challenging to assess broader health outcomes. Other common indicators of health outcomes include life expectancy [48] and child health status [49]. Healthcare services should also be economically efficient, as medical costs are an important factor affecting public access to healthcare [48]. Therefore, healthcare output measurements must consider the medical costs associated with healthcare utilisation [50]. Consequently, this study divided healthcare output into two dimensions (economic burden and health status) and selected the corresponding tertiary indicators.

Healthcare effectiveness

Healthcare effectiveness refers to the efficient use of healthcare resources to enhance the overall performance of the healthcare system [2]. A high-performing healthcare system should be able to provide effective institutional operations and medical services at lower costs [48]. Healthcare effectiveness is commonly measured using indicators such as bed utilisation [33], prenatal examination, and hospital delivery rates [2]. In China, where healthcare institutions are responsible for their own finances, bed turnover rates, the average number of patients treated per physician per day, and the average number of inpatient bed days per physician are important indicators of institutional operational efficiency [51]. The prevention and control of infectious diseases also reflect the performance of public health [2]. Therefore, this study divided healthcare effectiveness into three dimensions: healthcare service utilisation, healthcare operational efficiency, and health environment and disease prevention.

Figure 1 illustrates the four dimensions of the evaluation index system and their alignment with the Donabedian model, and Table 2 lists its indicators.

Methods

Model design

While the high-performing healthcare evaluation index comprises many indicators, many vary over a short period and cannot be effectively evaluated using the classical small model approach. Therefore, we examined each dimension's evolutionary pathway and interaction mechanisms in this index based on a multilevel structural dynamic factor model.

A core assumption of this multilevel structural dynamic factor model is that the variability in the observed variables stems from unobservable factors at different levels [52]. As shown in model (1), we employed a model to decompose the fluctuation of each indicator into a global factor, a local factor, and an idiosyncratic factor. Among them, the global factor measures the comprehensive performance of the healthcare system, the local factor measures the overall performance of healthcare services in a particular dimension, and the idiosyncratic factor is only affected by a single indicator.

$$\begin{aligned} y_{jt}^k = {} & \lambda_{j1}^G g_{1t} + \lambda_{j2}^G g_{2t} + \cdots \lambda_{jM}^G g_{Mt} + \lambda_{j1}^{F_k} f_{1t}^k \\ & + \lambda_{j2}^{F_k} f_{2t}^k + \cdots \lambda_{jN_k}^{F_k} f_{N_k t}^k + \mu_{jt}^k \\ & k = 1,2,\cdots,K;\ j = 1,2,\cdots,J_k;\ t = 1,2,\cdots,T \end{aligned} \tag{1}$$

Where y_{jt}^k represents the j^{th} observation of dimension k in the high-performing healthcare evaluation index in period t, g_{it} is the i^{th} global factor of the index in period t, f_{lt}^k is the l^{th} local factor of dimension k in period t, μ_{jt}^k is the idiosyncratic factor of the j^{th} observation of dimension k in period t, and λ_{ji}^G and $\lambda_{jl}^{F_k}$ are the factor loadings of the global factor of y_{jt}^k and the local factor of dimension k, respectively.

Per model (1), the observed indicators of dimension k are affected by the local and global factors in the healthcare system. This model decomposes the fluctuation of high-performing healthcare evaluation indicators and reduces the observed indicators of each dimension.

If we set:

$$\mathbf{Y}_t^k = (y_{jt}^k)_{J_k \times 1},\ k = 1,2,\cdots,K;\ j = 1,2,\cdots,J_k;\ t = 1,2,\cdots,T$$

$$\mathbf{G}_t = (g_{it})_{M \times 1},\ \ i = 1,2,\cdots,M;\ t = 1,2,\cdots,T$$

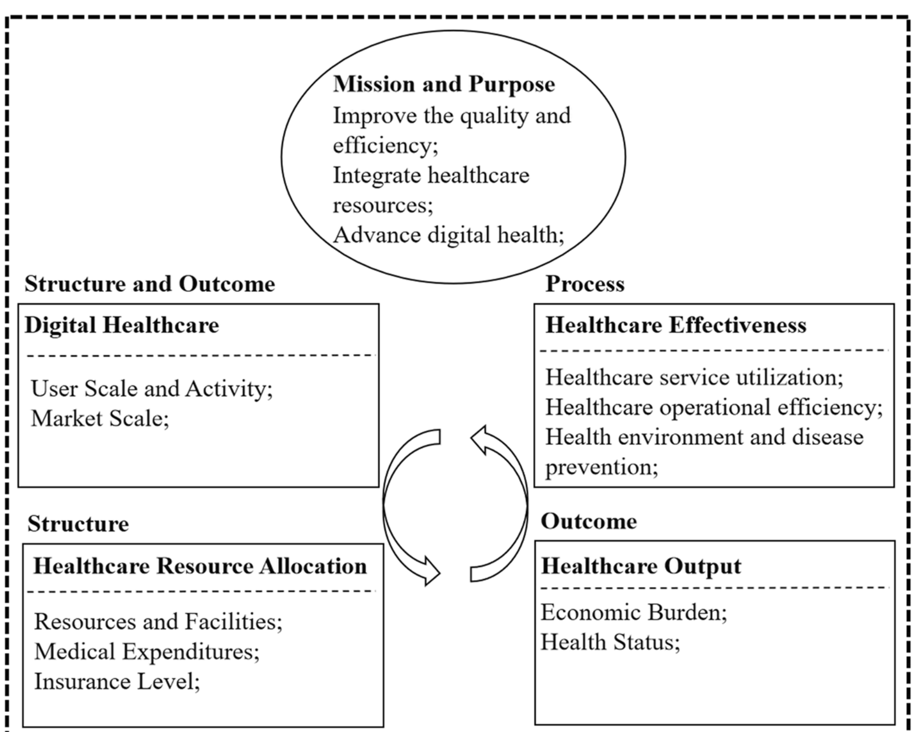

Fig. 1 The conceptual framework of the high-performing healthcare evaluation index

Table 2 High-performing healthcare evaluation index system

Dimension	Secondary Indicators	Tertiary Indicators
Digital healthcare	User scale and activity	Internet medical user scale
		Internet medical user utilisation rate
	Market scale	Online pharmaceutical retail sales
		Intelligent healthcare market scale
		Online consultation market scale
Healthcare resource allocation	Resources and facilities	Number of beds in health institutions
		Total area of healthcare facilities
		Total value of equipment for medical and health institutions
	Medical expenditures	Government health expenditures
		Social health expenditures
		Personal health expenditures
		Total assets of health institutions
	Insurance coverage	Number of employees insured
		Number of insured persons in urban and rural areas
		Income of the medical insurance fund
		Cumulative balance of the health insurance fund
Healthcare output	Economic burden	Per capita medical costs for outpatients
		Per capita medical expenses for hospitalised patients
	Health status	Infant mortality rate
		Maternal mortality rate
		Prevalence of low birth weight among children aged < 5 years
		Life expectancy per capita
Healthcare effectiveness	Healthcare service utilisation	Prenatal screening rate
		Rate of hospitalised births
		Number of health education activities conducted
		Annual hospitalisation rate of the population
		Bed utilisation rate
	Healthcare operational efficiency	Number of discharges per bed
		Average number of consultations per day by physicians
		Average number of inpatient bed days per physician per day
		Number of bed turnovers
	Health environment and disease prevention	Morbidity rate for category A and B infectious diseases
		Drinking water hygiene monitoring pass rate

$$\mathbf{F}_t^k = (f_{lt}^k)_{N_k \times 1},\ \ k = 1, 2, \cdots, K\ ;\ l = 1, 2, \cdots, N_k,\ t = 1, 2, \cdots, T$$

$$\boldsymbol{\mu}_t^k = (\mu_{jt}^k)_{J_k \times 1},\ \ k = 1, 2, \cdots, K\ ;\ j = 1, 2, \cdots, J_k\ ;\ t = 1, 2, \cdots, T$$

Then, model (1) can be expressed as:

$$\mathbf{Y}_t^k = \boldsymbol{\Lambda}^k \begin{bmatrix} \mathbf{G}_t \\ \mathbf{F}_t^k \end{bmatrix} + \boldsymbol{\mu}_t^k\ ,\ k = 1, 2, \cdots, K;\ t = 1, 2, \cdots, T \quad (2)$$

In model (2), $\boldsymbol{\Lambda}^k = [\boldsymbol{\Lambda}_G^k, \boldsymbol{\Lambda}_F^k]\ ,\ k = 1, 2, \cdots, K,$ where $\boldsymbol{\Lambda}_G^k = (\lambda_{ji}^G)_{J_k \times M}$. Model (2) aligns with the following assumptions [52]:

(i) $\boldsymbol{\Lambda}_G^k$ and $\boldsymbol{\Lambda}_F^k$ are lower triangular matrices with positive diagonal elements and $\boldsymbol{\Lambda}^k$ is the full column rank;
(ii) $E(\boldsymbol{\mu}_t^k | \mathbf{F}_t^1, \mathbf{F}_t^2, \cdots, \mathbf{F}_t^K) = 0,\ \ k = 1, 2, \cdots, K\ ;$
(iii) $E(\boldsymbol{\mu}_t^k \boldsymbol{\mu}_t^i | \mathbf{F}_t^1, \mathbf{F}_t^2, \cdots, \mathbf{F}_t^K) = 0,\ i \neq k = 1, 2, \cdots, K;$
(iv) $E(\mu_{jt}^k \mu_{it}^k | \mathbf{F}_t^1, \mathbf{F}_t^2, \cdots, \mathbf{F}_t^K) = 0,\ \ k = 1, 2, \cdots, K\ ;\ i \neq j = 1, 2, \cdots, J_k;\ t = 1, 2, \cdots, T$; and
(v) a serial correlation may exist between μ_{jt}^k in different periods.

In addition, the global factor $\mathbf{G}_t$ and local factor $\mathbf{F}_t$ obey the VAR(1) process:

$$\begin{bmatrix} \mathbf{G}_t \\ \mathbf{F}_t \end{bmatrix} = \boldsymbol{\Psi} \begin{bmatrix} \mathbf{G}_{t-1} \\ \mathbf{F}_{t-1} \end{bmatrix} + \boldsymbol{\eta}_t,\ \ t = 1, 2, \cdots, T \quad (3)$$

Where $\mathbf{F}_t = (\mathbf{F}_t^1, \mathbf{F}_t^2, \cdots, \mathbf{F}_t^K)'$. Model (3) satisfies the following assumptions:

(i) $\boldsymbol{\eta}_t = \begin{bmatrix} \boldsymbol{\eta}_{tG} \\ \boldsymbol{\eta}_{tF} \end{bmatrix} \overset{iid}{\sim} N(0, \begin{bmatrix} \boldsymbol{\sigma}_G^2 & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\sigma}_F^2 \end{bmatrix}),\ t = 1, 2, \cdots, T$; and

(ii) $\boldsymbol{\eta}_t$ and $\boldsymbol{\mu}_t$ and their lag orders are independent, and the variances of both $\boldsymbol{\eta}_{tG}$ and $\boldsymbol{\eta}_{tF}$ are unit matrices.

The non-zero elements of matrix $\boldsymbol{\Psi}$ in model (3) indicate that the index's dimensions are affected by their performance in the previous period and the prior performance of the other dimensions. The collective interaction of the dimensions determines the comprehensive performance of the healthcare system.

This study used RStudio for Gibbs sampling and Kalman filtering methods to estimate the parameters of models (1) and (2) above.

If we set:

$$\mathbf{Y}_t = (\mathbf{Y}_t^1, \mathbf{Y}_t^2, \cdots, \mathbf{Y}_t^K)',\ t = 1, 2, \cdots, T$$

$$\mathbf{X}_t = (\mathbf{G}_t, \mathbf{F}_t)',\ t = 1, 2, \cdots, T$$

$$\boldsymbol{\mu}_t = (\boldsymbol{\mu}_t^1, \boldsymbol{\mu}_t^2, \cdots, \boldsymbol{\mu}_t^K)',\ t = 1, 2, \cdots, T$$

Then, models (2) and (3) can be expressed as:

$$\mathbf{Y}_t = \boldsymbol{\Lambda}\mathbf{X}_t + \boldsymbol{\mu}_t,\ t = 1, 2, \cdots, T \tag{4}$$

$$\mathbf{X}_t = \boldsymbol{\Psi}\mathbf{X}_{t-1} + \boldsymbol{\eta}_t,\ t = 2, 3, \cdots, T \tag{5}$$

$\boldsymbol{\mu}_t \sim iid.N(\mathbf{0}, \mathbf{R})$, $\boldsymbol{\eta}_t \sim iid.N(\mathbf{0}, \mathbf{Q})$. The covariance matrix of $\mathbf{X}_t$ is $\mathbf{P}_{t|K} = var(\mathbf{X}_t | \mathbf{Y}_1, \mathbf{Y}_2, \cdots, \mathbf{Y}_K)$. The key steps in Kalman filter estimation include prediction and correction. First, the factor levels and their corresponding covariance matrix are predicted:

$$\mathbf{X_{t|t-1}} = \boldsymbol{\Psi}\mathbf{X_{t-1}},\ t = 2, 3, \cdots, T$$

$$\mathbf{P_{t|t-1}} = \boldsymbol{\Psi}\mathbf{P_{t-1|t-1}}\boldsymbol{\Psi}' + \mathbf{Q},\ t = 2, 3, \cdots, T$$

The predicted values $\mathbf{X}_{t|t-1}$ and $\mathbf{P}_{t|t-1}$ are then corrected using the observed indicator $\mathbf{Y}_t$:

$$\mathbf{X}_t = \mathbf{X}_{t|t-1} + \mathbf{K}_t(\mathbf{Y}_t - \boldsymbol{\Lambda}\mathbf{X}_{t|t-1}),\ t = 2, 3, \cdots, T$$

$$\mathbf{P}_{t|t} = (\mathbf{I} - \mathbf{K}_t\boldsymbol{\Lambda})\,\mathbf{P}_{t|t-1},\ t = 2, 3, \cdots, T$$

$$\mathbf{K}_t = \mathbf{P}_{t|t-1}\boldsymbol{\Lambda}'\left(\boldsymbol{\Lambda}\mathbf{P}_{t|t-1}\boldsymbol{\Lambda}' + \mathbf{R}\right)^{-1} = \mathbf{P}_{t|t}\boldsymbol{\Lambda}'\mathbf{R}^{-1}$$

Where $\mathbf{K}_t$ is the Kalman gain.

Since Gibbs sampling can converge to the true values of the parameters independent of the prior distribution, this study used the multivariate normal distribution as the a priori distribution of the model parameters, with 5000 Gibbs burn-in-stage samples and 15,000 samples. Please see the Supplementary Material for details of the parameter estimation results.

Data sources and processing

The digital healthcare data were obtained from the China Internet Network Information Center and the China Business Industry Research Institute website. The data on resources and facilities and the economic and expenditure aspects of the healthcare resource allocation dimension were obtained from the RESSET database. The insurance coverage data were obtained from the official website of the National Healthcare Security Administration. The healthcare output and effectiveness data were obtained from the China Statistical Yearbook and the Statistical Information Center. The high-performing healthcare evaluation index comprises four primary and 33 observation indicators covering the period from 2017 to 2023: $T = 7$, $K = 4$, and $\sum_{k=1}^{5} J_k = 33$ in model (2). In addition, we regarded $\mathbf{G}_t$ and $\mathbf{F}_t^k$ as one-dimensional to ensure that the local and global factors have greater economic meaning.

In addition, due to missing data for some indicators (e.g. the number of health education activities conducted in China in 2020), we employed cubic spline interpolation to estimate the missing data and complete the data for some indicators for 2022 and 2023 based on the grey prediction model.

We also standardised the raw data to eliminate the influence of the indicator scale. If X_{it} is a positive indicator, the normalisation process is: $\tilde{X}_{it} = (X_{it} - X_i^{Min})/(X_i^{Max} - X_i^{Min})$. If X_{it} is a negative indicator, the normalisation process is: $\tilde{X}_{it} = (X_i^{Max} - X_{it})/(X_i^{Max} - X_i^{Min})$. Where X_i^{Max} and X_i^{Min} are the indicator's maximum and minimum values within the study period.

Table 3 presents a descriptive statistical analysis of the tertiary indicators in the high-performing healthcare evaluation index system for China. It shows the maximum, minimum, mean, and standard deviation of each indicator from 2017 to 2023 (i.e. the distribution of the values of each indicator). Given the mean, a larger standard deviation indicates greater fluctuation in the indicator). Table 3 offers an intuitive description of the current state of China's national healthcare system and lays the foundation for further discussion of the evolutionary pathways and interaction mechanisms of each dimension.

Table 3 Descriptive analysis of the high-performing healthcare system evaluation index

Tertiary Indicators	maximum	minimum	mean	standard deviation
Internet medical user scale	41393.00	10515.16	24318.86	11753.28
Internet medical user utilisation rate	0.38	0.20	0.27	0.07
Online pharmaceutical retail sales	622.00	70.00	292.43	213.52
Intelligent healthcare market scale	62.85	4.87	23.13	20.53
Online consultation market scale	515.00	30.00	216.29	178.36
Number of beds in health institutions	1014.29	794.03	908.50	76.88
Total area of healthcare facilities	1204.09	790.94	979.22	151.07
Total value of equipment for medical and health institutions	21850.22	11321.67	16241.12	3754.80
Government health expenditures	25971.08	15205.87	20303.91	3967.70
Social health expenditures	41787.45	22258.81	31751.48	6887.54
Personal health expenditures	24652.33	15133.60	19921.63	3329.84
Total assets of health institutions	711870118.00	349619767.53	496794387.39	125276828.11
Number of employees insured	37093.88	30802.50	34087.77	2365.24
Number of insured persons in urban and rural areas	104.39	96.29	101.00	2.79
Income of the medical insurance fund	33355.16	19246.34	25909.57	5153.17
Cumulative balance of the health insurance fund	47755.56	20003.43	32592.39	10143.52
Per capita medical costs for outpatients	367.60	257.00	312.24	39.56
Per capita medical expenses for hospitalised patients	11649.25	8890.70	10308.91	994.62
Infant mortality rate	6.80	4.55	5.48	0.77
Maternal mortality rate	19.60	14.98	17.05	1.61
Prevalence of low birth weight among children aged < 5 years	1.40	1.03	1.18	0.20
Life expectancy per capita	79.10	76.70	77.84	0.89
Prenatal screening rate	98.28	96.50	97.30	0.68
Rate of hospitalised births	99.93	99.90	99.90	0.01
Number of health education activities conducted	31.98	6.15	15.21	10.29
Annual hospitalisation rate of the population	19.03	16.13	17.35	1.07
Bed utilisation rate	85.00	65.62	76.34	7.92
Number of discharges per bed	30.70	22.45	24305.56	3.36
Average number of consultations per day by physicians				
Average number of inpatient bed days per physician per day	8.20	6.43	7.35	0.72
Number of bed turnovers	1.90	1.37	1.66	0.21
Morbidity rate for category A and B infectious diseases	32.30	23.74	28.46	3.52
Drinking water hygiene monitoring pass rate	222.06	165.21	197.71	23.74

Results

Evolutionary pathway of China's high-performing national healthcare system

We employed a multilevel structural dynamic factor model to estimate the global factor (GloFactor) of China's high-performing national healthcare system and the local factor of each dimension to examine the evolutionary pathway of the overall system and its dimensions. The GloFactor was jointly influenced by the performance of each dimension and its interaction; it measured the comprehensive performance of China's high-performing national healthcare system. The local factor for healthcare resource allocation (MRFactor) reflects the overall status of traditional medical resources and facilities, medical expenditures, and insurance coverage. The local factor for digital healthcare (DMFactor) reflects the development level of the digital healthcare market size and user scale. Similarly, the HOFactor and IPFactor reflect the overall performance of healthcare output and healthcare effectiveness, respectively.

This study measured the global factor of China's high-performing national healthcare system and the local factors of each dimension from 2017 to 2023 based on the previously described multilevel structural dynamic factor model. Figure 2 shows the development trend of each factor, revealing the evolutionary pathway of China's high-performing national healthcare system and each dimension.

The GloFactor of China's high-performing national healthcare system shows an increasing trend, while the evolution pathways of the local factors in each dimension differ significantly. The increasing GloFactor indicates continued improvements in the overall performance of China's high-performing national healthcare system and that the reform of China's healthcare system has been effective. Among the local factors, the DMFactor shows an increasing trend, reflecting improvements in digital

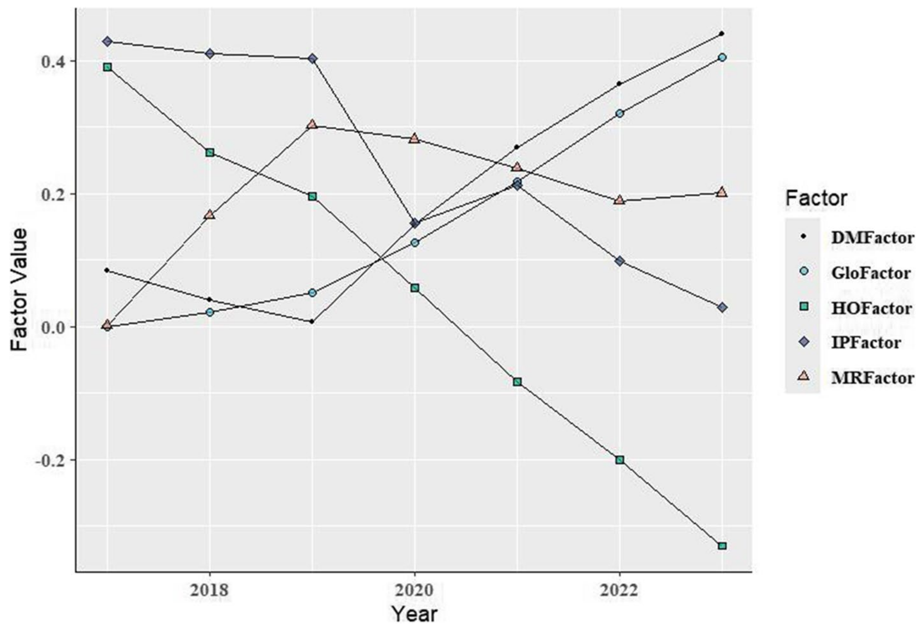

Fig. 2 Evolutionary pathway of China's high-performing national healthcare system from 2017 to 2023

healthcare. This trend, indicated by various indicators, may reflect the expansion of the digital healthcare market and the increase in the public's online medication purchases. Unlike the DMFactor, the MRFactor shows a more moderate increase, increasing significantly before 2019 and stabilising afterwards. This trend implies that healthcare resource allocation in China's high-performing national healthcare system peaked in 2019, and further optimisation requires additional policy design and support.

In contrast, the HOFactor and IPFactor showed a continuous decreasing trend. The increase in life expectancy and decreases in various mortality rates suggest improving healthcare output. However, increasing per-visit medical costs for outpatients and inpatients may cause an imbalance between healthcare output costs and health outcomes, leading the HOFactor to decrease. The IPFactor may be decreasing due to reduced resource utilisation efficiency. Despite significant improvements in the health environment and disease prevention, the decrease in physicians' daily consultations and hospital bed turnovers reflects a decrease in traditional medical service efficiency, impacting the overall performance of healthcare effectiveness.

Despite these declines, the reform of China's high-performing national healthcare system has achieved notable success, as the GloFactor and DMFactor have increased steadily. The primary concern is that the performance of traditional healthcare services is inconsistent with policy expectations, particularly regarding healthcare output. Incorporating digital healthcare services constitutes an important approach to realising a high-performing national healthcare system. However, the evolutionary pathways of the IPFactor and HOFactor indicate that digital healthcare has not evolved in the same direction as the healthcare output and effectiveness of traditional healthcare. Therefore, we explored the interaction mechanisms of the dimensions of China's high-performing national healthcare system using impulse response functions.

Interaction mechanisms of China's high-performing national healthcare system

Since the dimensions in high-performing national healthcare systems are interrelated and interact. Changes due to the external environment or the performance of other dimensions will lead to the adjustment of all dimensions. According to complex systems theory, when a positive external shock suddenly hits a dimension in the system, the other dimensions respond in two ways: positive and negative feedback. Positive external shocks refer to changes in external variables that positively impact the system, while negative external shocks refer to changes in external variables that negatively impact the system. Possible sources of positive external shocks are policy development or sudden increases in healthcare demand. For example, a sudden infectious disease outbreak may substantially increase healthcare output, and such a shock may enhance the performance of both the healthcare effectiveness and healthcare resource allocation dimensions.

We use impulse response analysis to quantify the impact of different shocks on the model, thereby revealing the interactions between various factors and their contributions to the evolution of the system. If a positive synergistic relationship exists between two dimensions, a positive feedback relationship will manifest as a positive impulse response outcome. If a conflict of resources or short-term interests exists between two dimensions, a negative feedback relationship will manifest as a negative impulse response outcome.

The model used in this study can uncover the complex dynamic interaction network among the examined factors. The non-zero elements in the matrices of model (3) indicate that each dimension of China's high-performing national healthcare system is not only influenced by its own performance in the previous period but also by the performance of other dimensions in the previous period. In addition, the interactions among the factors are asymmetric. For example, the impact of an external shock to the DMFactor on the IPFactor differs in both the path and magnitude from the impact of an external shock to the IPFactor on the DMFactor. This asymmetry reflects the complex interactions among the factors. When the DMFactor experiences an external shock, its impact on the IPFactor includes not only its direct effect on the IPFactor but also indirect effects transmitted through other factors.

Moreover, when the confidence interval of the impulse response does not contain zero, the positive or negative feedback is considered significant at this point. Therefore, examining the interaction mechanisms of the dimensions of China's high-performing national healthcare systems can lead to a better understanding of its evolutionary pathway and its deviation relative to policy expectations. Figures 3, 4, 5, 6, 7 and 8 reveal the direction and magnitude of the interactions among the dimensions of China's high-performing national healthcare system when they experience sudden positive external shocks.

Interaction mechanisms between global and local factors

Figure 3 shows the impulse responses of the GloFactor when the four dimensions of China's high-performing national healthcare system are subjected to a positive external shock of one unit of standard deviation. When the performance of all four dimensions improves, they all positively affect the GloFactor, but this positive effect gradually fades after one year. Therefore, realising a high-performing national healthcare system requires

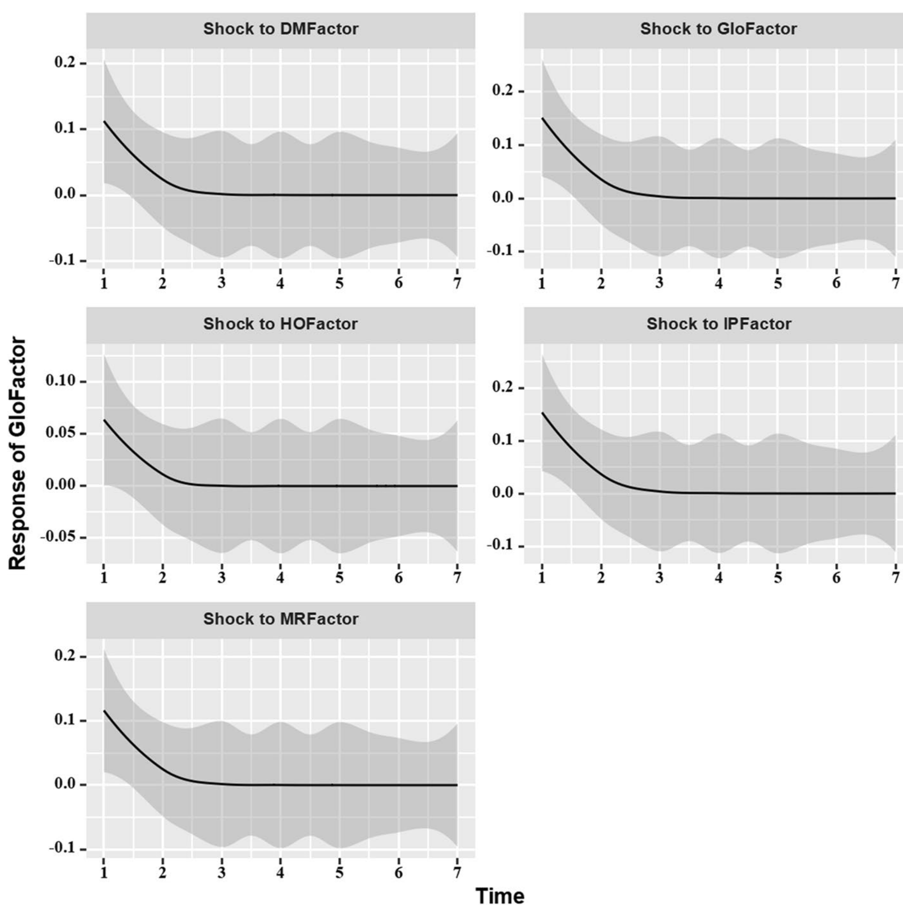

Fig. 3 Impulse responses of the GloFactor when each dimension experiences a positive external shock

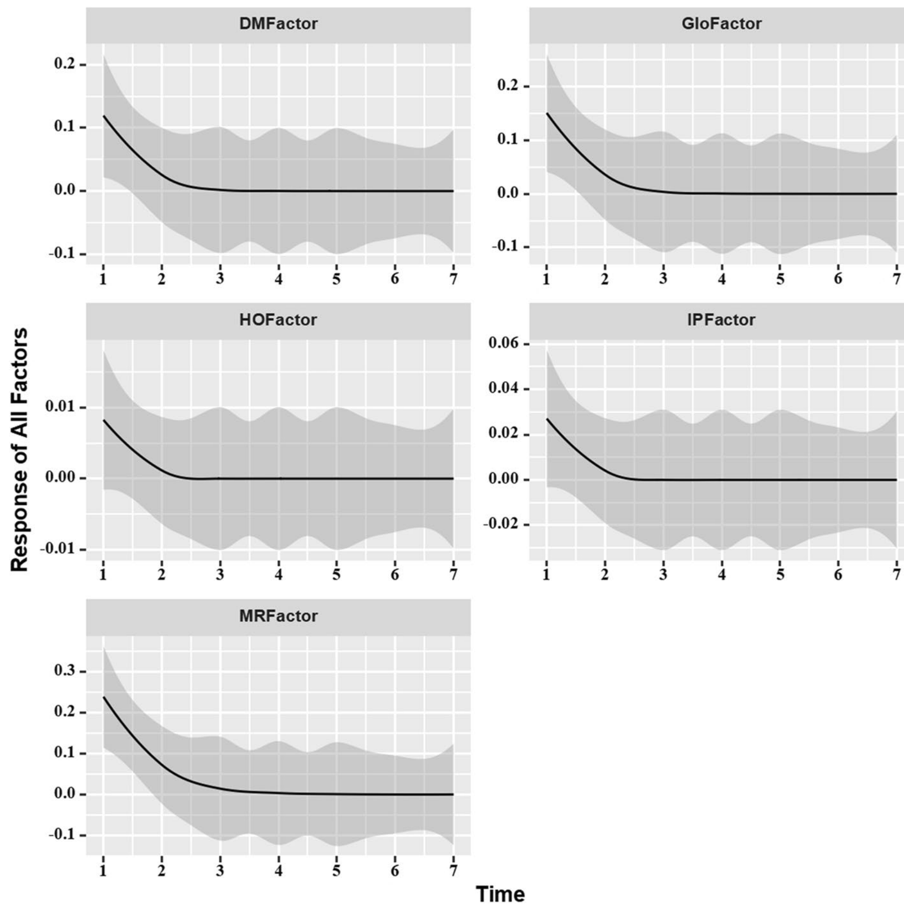

Fig. 4 Impulse responses of each dimension when the GloFactor experiences a positive external shock

continuous improvement in all healthcare dimensions. Figure 3 also shows that the IPFactor has the greatest impact on the GloFactor, indicating that healthcare effectiveness is critical to the healthcare system. In contrast, the HOFactor has the smallest impact on the GloFactor, indicating that simply improving healthcare output has only a minimal effect on improving the overall performance of the healthcare system during the study period.

Figure 4 reveals the impulse responses of each dimension when the GloFactor is subjected to a positive external shock of one standard deviation unit. The MRFactor was the most affected, followed by the DMFactor. In contrast, the HOFactor and IPFactor were not significantly affected. This observation suggests that improvements in the overall performance of China's high-performing national healthcare system promote the performance of healthcare resource allocation and digital healthcare but not of healthcare output and effectiveness, possibly because improving healthcare output and effectiveness requires more input resources. Therefore, neither can be effectively improved in the short term.

Interaction mechanisms between digital healthcare and other traditional healthcare services

Figure 5(a) shows the impulse responses of the DMFactor when the other healthcare dimensions are subjected to a positive external shock of unit standard deviation. The MRFactor had the greatest impact on the DMFactor. A positive external shock to the MRFactor, such as increasing healthcare facilities or rationally allocating healthcare resources, promotes improvements in digital healthcare. In addition, a positive external shock to the HOFactor, such as a sudden increase in healthcare demand, promotes improvements in digital healthcare. However, a positive external shock to the IPFactor does not significantly impact the DMFactor. Therefore, improvements in healthcare effectiveness do not impact the market size and user activity of digital healthcare.

Figure 5(b) shows the impulse responses of the other dimensions when the DMFactor is subjected to a positive external shock of unit standard deviation. The DMFactor had the greatest impact on the IPFactor, suggesting that an increase in the market size or user scale of digital healthcare promotes healthcare effectiveness. When Fig. 5(a) and (b) are compared, it becomes apparent that

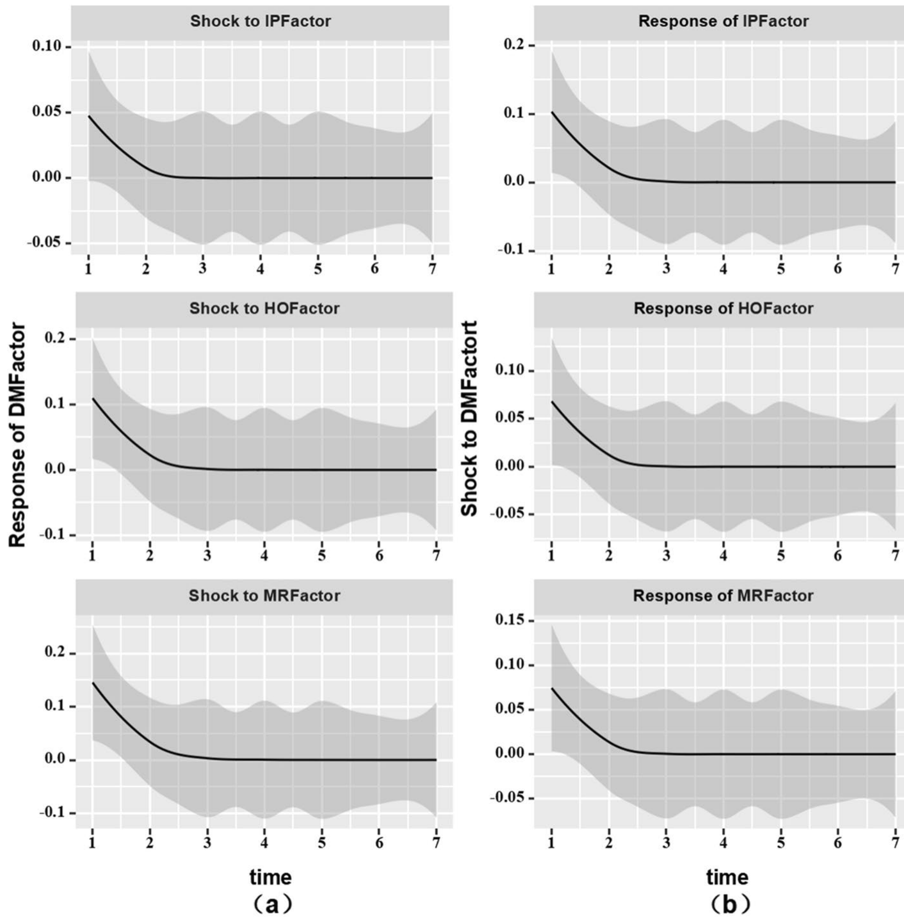

Fig. 5 Impulse responses of (**a**) the DMFactor and (**b**) the other dimensions to a positive external shock

while improvements in the MRFactor and HOFactor lead to improvements in the DMFactor, improvements in the DMFactor lead to smaller improvements in the MRFactor and HOFactor. Therefore, overemphasising the importance of digital healthcare may overestimate its role in building high-performing national healthcare systems.

Interaction mechanisms between healthcare resource allocation and the other dimensions

Figure 6(a) shows the impulse responses of the MRFactor when the other dimensions are subjected to a positive external shock of unit standard deviation. Figure 6(b) shows the impulse responses of the other dimensions when the MRFactor is subjected to a positive external shock of unit standard deviation. When Fig. 6(a) and (b) are compared, it is evident that stronger bidirectional relationships have been formed between DMFactor and MRFactor and between IPFactor and MRFactor. In addition, the HOFactor is most affected by a positive external shock to the MRFactor, but a positive external shock to the MRFactor does not significantly affect the HOFactor. Therefore, an increase in healthcare output increases the demand for healthcare resource allocation, but an increase in healthcare resource allocation alone does not significantly increase health output.

Interaction mechanisms between healthcare output and the other dimensions

Figure 7(a) shows the impulse responses of the HOFactor when the other dimensions are subjected to a positive external shock of one unit of standard deviation. Figure 7(b) shows the impulse responses of the other dimensions when the HOFactor is subjected to a positive external shock of one unit of standard deviation. Figure 7 shows that a positive external shock to the DMFactor and the MRFactor does not significantly impact the HOFactor. However, a positive external shock to the HOFactor promotes improvements in the MRFactor and DMFactor. In addition, a stronger bidirectional relationship exists between HOFactor and IPFactor.

Interaction mechanisms between healthcare effectiveness and the other dimensions

Figure 8(a) shows the impulse responses of the IPFactor when the other dimensions are subjected to a positive external shock of one unit standard deviation. Figure 8(b)

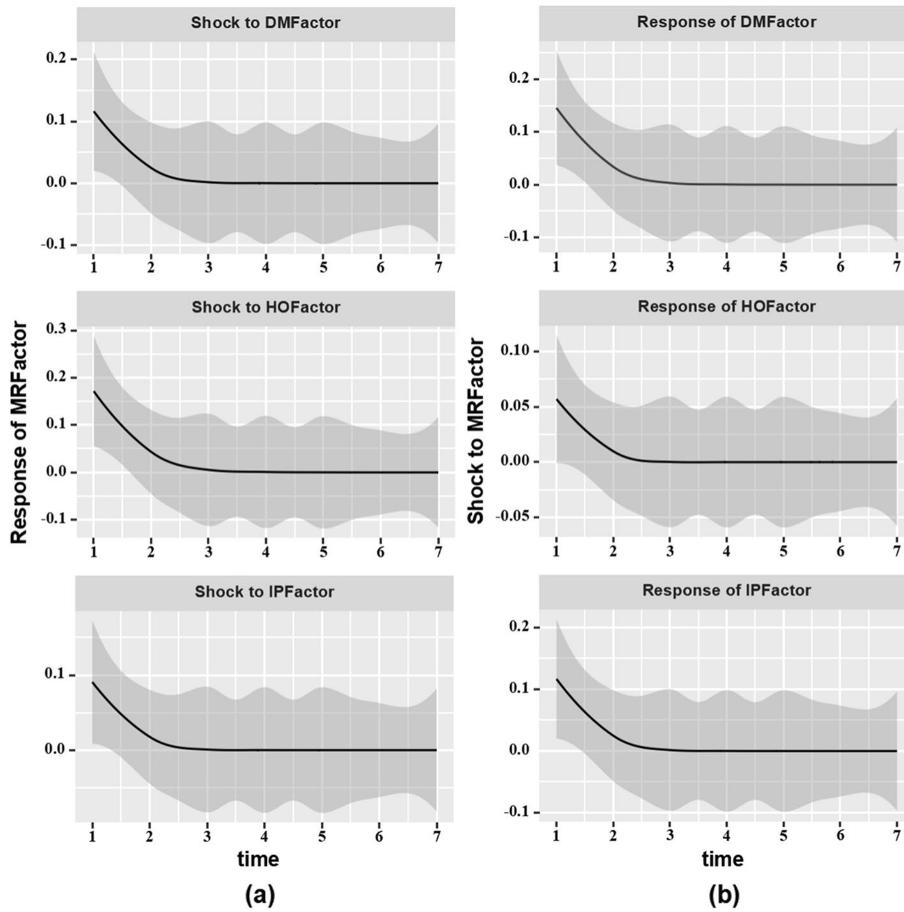

Fig. 6 Impulse responses of the (**a**) MRFactor and (**b**) the other healthcare dimensions to a positive external shock

shows the impulse responses of the other dimensions when the IPFactor is subjected to a positive external shock of one standard deviation unit. A positive external shock to the DMFactor, MRFactor, and HOFactor significantly and positively affected the IPFactor, with the HOFactor having the greatest effect. A sudden increase in healthcare output enhances healthcare effectiveness in the short term. Notably, an increase in healthcare effectiveness can drive the optimisation of healthcare resource allocation but does not significantly affect digital healthcare.

Discussion and conclusions

High-performing healthcare has become a key focus in many countries. The key to developing a high-performing healthcare system is to balance the social and economic attributes of healthcare services [3]. However, there remains no consistent definition of high-performing healthcare or a proven measurement framework [7], leading to diverse reforms across countries aimed at providing high-performing healthcare. In addition, healthcare systems are complex, as their overall performing depends on the interactions of internal agents [25], and these interactions are non-linear [23]. Notably, the widespread adoption of digital technologies is likely to impact existing organisational structures [14]. Exploring the interactions between digital healthcare and traditional healthcare activities is essential for understanding the dynamic evolutionary characteristics of high-performing healthcare in the context of digitalisation.

This study aimed to reveal the evolutionary pathway of China's high-performing national healthcare system. It developed and utilised a high-performing national healthcare evaluation index comprising four dimensions: digital healthcare, healthcare resource allocation, healthcare output, and healthcare effectiveness. Based on existing research, this study defined a high-performing national healthcare system as a dynamic evolutionary system that can provide timely, effective, and efficient healthcare services. Healthcare systems are complex and unstable; their inputs, processes, and outcomes are always dynamic and interactive. The developed high-performing national healthcare evaluation index integrates digital and traditional healthcare services into a unified measurement framework containing ten secondary and 33 tertiary indicators and covering healthcare human and

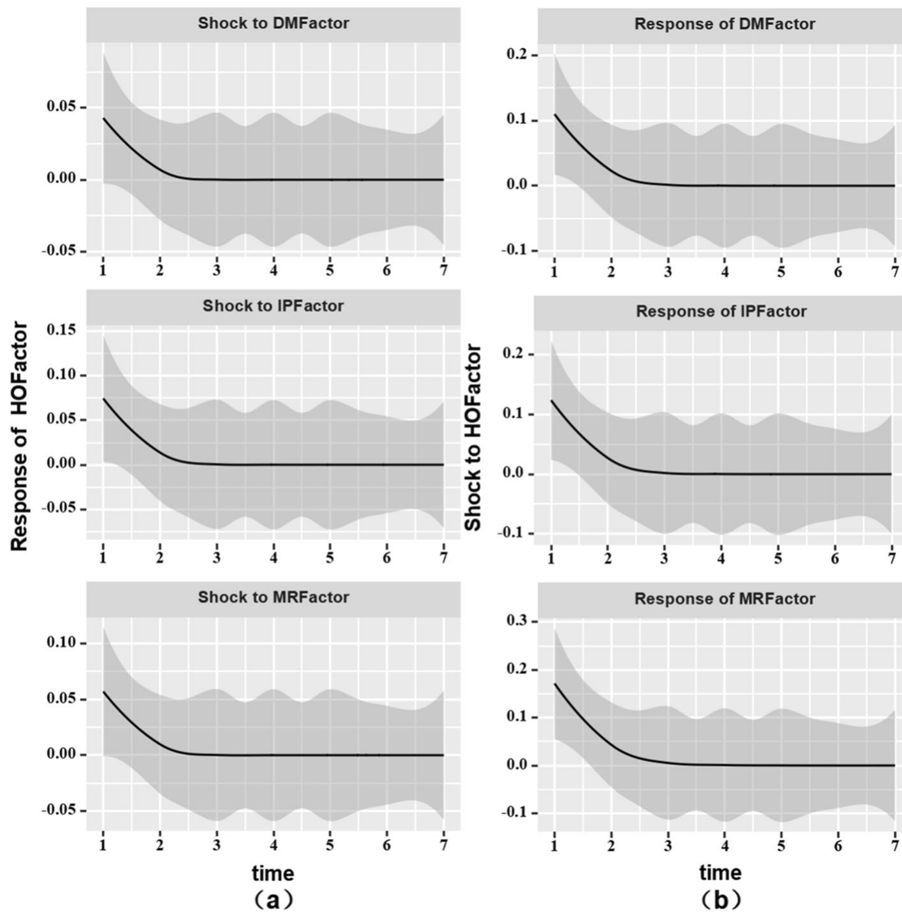

Fig. 7 Impulse responses of (**a**) the HOFactor and (**b**) the other dimensions to a positive external shock

material resources, healthcare costs, and the quantity and efficiency of healthcare outputs.

The multilevel dynamic factor model employed in this study indicated that the evolutionary pathways of the global and local factors of China's high-performing national healthcare system are not entirely consistent with the policy expectations of the technology-enabled healthcare reform. The coexistence of idle and insufficient medical resources in primary healthcare institutions and large general hospitals is a long-standing contradiction in China's healthcare system [28]. China has adopted the sharing and collaboration of medical resources as a core means of establishing a high-performing healthcare system [53]. China's '14 th Five-Year Plan for National Health Informatization' also encourages medical institutions to use digital technologies to enhance their medical services [30]. However, the evolutionary pathways of the local factors for digital healthcare, healthcare output, and healthcare effectiveness are not aligned. While digital healthcare and healthcare resource allocation have increased significantly in China since 2017, healthcare output and effectiveness in traditional medical services have decreased, suggesting that technological development is not synonymous with social progress [54]. Digital transformation has an embedded nature, empowering actors to achieve their goals and visions [55]. The failure of traditional medical services to integrate digital healthcare may impede the value creation of digital healthcare [56].

This study explored the interaction mechanisms of the dimensions using impulse response functions to examine how the practices used to create a high-performing national healthcare system in China deviate from expectations. Our findings show that healthcare effectiveness is the most important factor in creating a high-performing national healthcare system in China, while healthcare output is the least important factor. The Chinese healthcare market's fee-for-service approach has left the issue of overmedication unresolved [51]. Establishing a high-performing national healthcare system in China must involve strengthening government regulation, and healthcare services should focus more on efficiency than the number of outputs. Studies have suggested that overall healthcare performance in China can be improved by promoting digital healthcare [11, 23]. This study found that when digital healthcare improves, healthcare

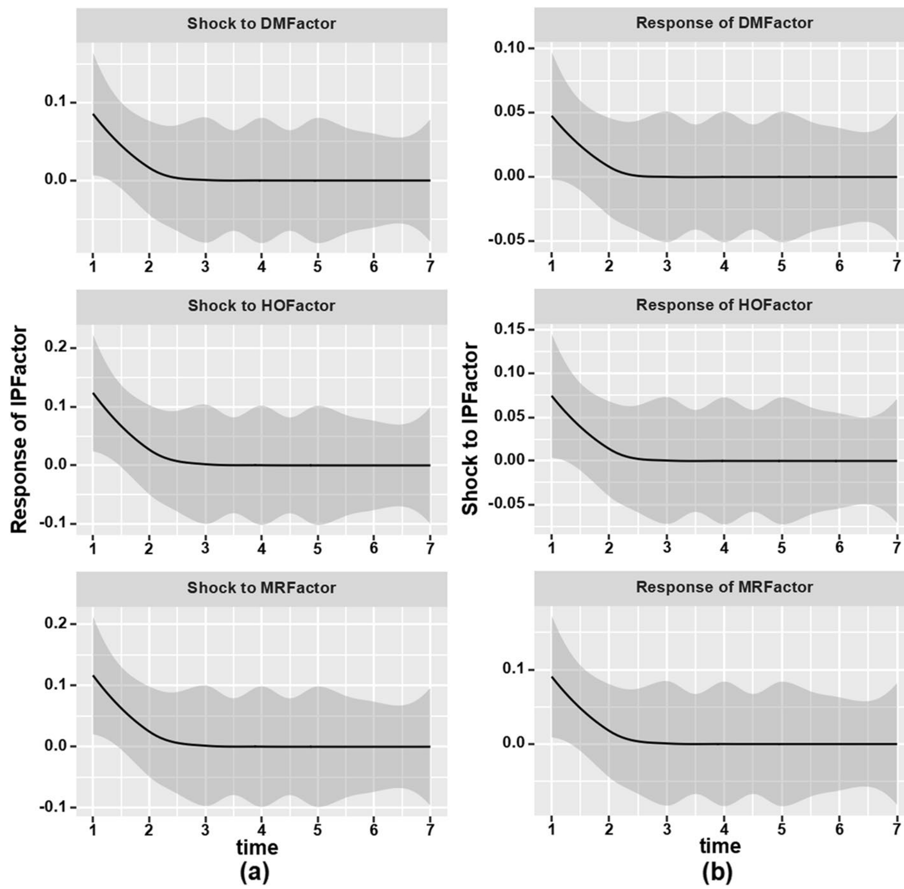

Fig. 8 Impulse responses of (**a**) the IPFactor and (**b**) the other dimensions to an external positive shock

effectiveness and overall healthcare significantly improve, confirming that promoting digital healthcare enhances healthcare effectiveness and overall healthcare performance. In contrast, digital healthcare has a weaker impact on healthcare resource allocation and output.

Overall, digital healthcare exhibited a weak bidirectional relationship with both healthcare resource allocation and healthcare output but a unidirectional relationship with healthcare effectiveness. Under the Donabedian model, healthcare resource allocation and the user scale and activity of digital healthcare correspond to the structure of healthcare, healthcare output and market scale in digital healthcare correspond to the outcome of healthcare, and healthcare effectiveness focuses more on the process of healthcare. The unidirectional relationship between digital healthcare and healthcare effectiveness indicates that developing digital healthcare can significantly enhance healthcare effectiveness (i.e. digital healthcare optimises the processes of traditional medical services). This finding is consistent with the findings of Ghosh et al. [14]. However, the weak bidirectional relationship of digital healthcare with both healthcare resource allocation and healthcare output suggests that digital healthcare primarily serves as a supplement to traditional healthcare structures and outcomes. Changes in traditional healthcare structures and outcomes are more easily transmitted to digital healthcare, while improvements in digital healthcare have a weaker supportive effect on traditional healthcare resource allocation and healthcare output. This finding indicates that the optimisation of traditional medical service processes and outcomes through digital healthcare is limited. Differences in healthcare resources and infrastructure may be significant barriers to the impact of digital healthcare on healthcare resource allocation and output.

This study suggests that digital healthcare contributes to enhanced system performance, but it also reveals the limitations of its impact on traditional medical services. Future policies and practices should focus more on optimising the traditional healthcare system, especially in improving healthcare resource allocation and output, while promoting the organic integration of digital and traditional healthcare.

The high-performing healthcare evaluation index developed in this study, based on the Donabedian model and incorporating digital healthcare, offers a valuable reference for other countries facing similar challenges in medical resource distribution and digital transformation to China. However, given that organisational structure, policy environment, and resource allocation vary significantly among healthcare systems in different countries, the developed index and conclusions of this study may require appropriate adjustments according to local goals and values when directly applied to other countries.

This research can be expanded through the following two approaches. Firstly, this study assumed that each factor obeyed the VAR(1) process. Future studies could improve our model and estimate the coefficient matrices among the factors more accurately. Secondly, this study focused on China's national healthcare system, and the context may differ from country to country. Future studies could explore the evolutionary characteristics of healthcare systems by incorporating heterogeneous factors (e.g. environment and healthcare structure).

Authors' contributions
Chong Feng: Conceptualization, Methodology, Writing. Feiyang Chen: Data curation, Original draft preparation. Ziwei Ye: Visualization, Original draft preparation. Fenling Zhang: Writing- Reviewing and Editing.

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Data availability
The original data can be queried on the official website of the National Healthcare Security Administration (https://www.nhsa.gov.cn/col/col7/index.html?uid=2599&pageNum=1), the China Statistical Yearbook (https://data.stats.gov.cn/easyquery.htm?cn=C01), the Statistical Information Center (http://www.nhc.gov.cn/mohwsbwstjxxzx/tjzxydsj/new_list.shtml), the RESSET database (https://www.resset.com/), the China Internet Network Information Center (https://www.cnnic.net.cn/6/86/88/index.html), and the website of the China Business Industry Research Institute (https://s.askci.com/).

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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