Knowledge Translation of Scholarly Publishing Impacts on Public Health

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Research

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Abstract

BACKGROUND: Although scholarly publishing plays a key role in learning, the role of knowledge translation of scholarly publishing with education and income on public health has not been well established. The objective was to describe how knowledge translation of scholarly publishing impacts on public health.

METHODS: The correlations between the input data and the target data were firstly calculated. After the input data that is not correlated to the target have been removed, the principal component analysis will be performed to avoid multicollinearity problems in the input data. Finally, the multivariate regression method is used to fit the relationship between the principal components and the target data. Thus both dimensionality reduction and personalized optimization oriented a target can be done.

RESULTS: After the public health in China is measured by Life expectancy and Death rate, the Pearson correlation coefficient, principal component analysis, and linear regression method have been performed. It proved that some activities of knowledge translation of scholarly publishing with a focus on health and well-being have the highest correlations with the first principal component. Results are also presented on that the first and the second principal component explain 99.3% of the variation ($p<0.01$) in Life expectancy and 92.8 % of the variation ($p<0.01$) in Death rate, respectively.

CONCLUSIONS: Scholarly publishing, education, income, health expenditure, nurses, and midwives appear to have a similarly important effect on public health.

Keywords: Scholarly Communication; Publications; Public Health; Principal Component Analysis; Regression Analysis; Multivariate Analysis

Background

Society can be treated as a system of exchanges that both the parties who make the exchange are benefited [1]. Knowledge plays various functional roles in society. Knowledge can be a basis for action. For example, once the causes of disease are identified, knowledge can be used to find a cure. Knowledge also licenses assertions and it can be used to policymakers, private companies, courts of law, etc. for making a proper decision. Knowledge is stored in papers, journals, books, proceedings, digital repositories, etc. Scientific knowledge came to mean the elimination of surprise and outlawed miracles. The stored knowledge (for example, published in scholarly journals and books, or stored in libraries, optic media, etc.) can be available for retrieval and use by anyone else [2]. The idea of the Invisible College for scholarly communication was originated by a group of scholars at Oxford University in the 1640s. The Invisible College was named as the Royal Society. But as the group grew, the journal became a suitable means to scholarly communication owing to the natural inhibitions, difficulties, and finance of traveling. The first journal named "Philosophical Transactions of the Royal Society of London" was published in March 1665. Now more ways to scholarly communication have been developed due to the advanced technology. However, journals have emerges as more than a device for scholarly communication in modern society [3].

Sustainable development might be described by complex interrelationships between natural and social spheres [4]. An accelerated and sustainable economic growth requires organizations to make proper managerial decisions and realizing actions and behaviors by obtaining the necessary knowledge at a high-quality level and using it with maxim effectiveness [5]. The knowledge of health and well-being is various. The health benefits of physical activity require the necessary knowledge, skills, etc. [6]. Changes in the accuracy of sea ice travel knowledge affect the ability of Inuit to be on the ice safely. These changes are transforming sea ice for Inuit from a place that is 'theirs', a place that means cultural and individual freedom and autonomy and is an important source of health [7]. Knowing colorectal cancer screening tests increases the relevant confidence and benefit perception [8]. Increasing knowledge and awareness by training health professionals to communicate and deliver targeted preconception care, which aims to enhance health status before conception to reduce perinatal morbidity and mortality and improve maternal and child health, interventions may be important [9]. Health promotion is not only related to the prevention of diseases, it is essential to invest in health education actions aiming at the sharing of knowledge, as well as the development of knowledge [10]. Lack of knowledge can cause serious health problems. The delays caused by lacking the knowledge to diagnose or suspect breast cancer are likely to

be worse [11]. Better-educated people have lower mortality, experience less often harmful diseases, and feel overall healthier than their less-educated peers [12]. This is because education raises a person's health knowledge, allowing the educated to choose a more efficient input mix in the health production process, i.e., to make better health decisions, leading to improved health outcomes [13].

Knowledge translation has been defined in various ways but has generally focused on the application of knowledge. For example, it is defined as "a dynamic and iterative process that includes the synthesis, dissemination, exchange and ethically sound application of knowledge to improve the health of populations, provide more effective health services and products and strengthen the health care system". The principles of knowledge translation can be described as 'dissemination', 'utilization', 'evidence into practice' and 'knowledge transfer' [14, 15]. Understanding local Indigenous processes of knowledge creation, dissemination, and utilization is a necessary prerequisite to effective knowledge translation in Indigenous contexts [16]. What is and what is not considered to be knowledge translation is the most important [17]. Knowledge translation in some circumstances has been found as effective as complex and multifaceted ones [18]. Definitions of concepts in knowledge translation are unclear [19, 20]. It results that information retrieval is difficult [21]. Making knowledge relevant to the challenges their stakeholders face, the capabilities of their stakeholders, and the expectations the government can make it work [22]. Knowledge translation in the health field strategies involved in public or community prevention orientated coalitions from a range of health and well-being disciplines [23], preventative adolescent substance abuse services [24], healthy body weight promotion [25], immunization and cancer screening prevention [26].

The research utilization theory of knowledge translation suggests that knowledge is a changing set of understandings shaped by those who both generate and use research [27]. It implied that potential users are more likely to do so if there is an identified need or incentive [28]. This is similar to the diffusion of innovations theory [29]. Potential adopters of innovations can be categorized as innovators, early adopters, early majority, etc. [30]. Many theories have varying objectives, which range from information provision individually or to large audiences to achieving behavior change through education or skills acquisition [31]. For example, the successes, challenges, and lessons learned from using social media within health research have been studied [32]. At the same time the knowledge gap have been to affect disseminate information in a social system [33,34]. More importantly, it is often difficult to measure directly the effects of knowledge creation and diffusion on society [35].

Methods

The data have been obtained from the website of the World Bank (https://data.worldbank.org) and the website of SCImago (https://www.scimagojr.com). One can note that the data used in this article do not include the influence of knowledge gaps. All data of the scholarly publishing (e.g., articles indexed by SCImago, journals indexed by SCImago, etc.), education, health, etc. in this article use the data for the entire Chinese community. This article aims to do a pioneer investigation on the relationship between knowledge translation from the research results published in the scholarly journals and the health and well-being of the whole Chinese society without considering the difference caused by knowledge gaps. In detail, the relationship has been statically analyzed based on the data of the research results published in the scholarly journals and the health and well-being data in recent years.

To check generating theories and hypotheses, it is very important for using data in testing those generating theories and hypotheses. To test most hypotheses, two variables (a proposed cause and a proposed outcome) need to be measured. Variables are things that can vary. After the data of the research have been collected, it is to analyze the data that involves both seeing what the general trends in the data are via graphical data and also fitting the data by using statistical models.

Many researchers have studied issues in the social sciences by using mathematical methods and statistic models. For example, regression and component analysis are so important and frequently used in social science research [36-42]. The principal component analysis, a mathematical method, can help us find relationships between two variables sets (a cause variable set and an outcome variable set) that have been collected for an issue in societies. For example, principal component analysis has been used to get socioeconomic impact [43]; the relationship between academic performance, substance use, sleep quality, and risk of anxiety and depression in young adults have been investigated by principal component analysis [44]; principal component analysis has also been used for analyzing the performance of semiconductor devices [45]; the relationships between some pre- and post-slaughter traits of broilers have been investigated by principal component analysis [46]; principal component analysis has also been used for early disease detection [47]; principal component analysis has also been used to predict ozone concentrations [48].

Multicollinearity is a linear association between two or more explanatory variables. A set of variables is perfectly multicollinear will have the following equation

$$\alpha_1 x_1 i + \alpha_2 x_{2i} + \Lambda + \alpha_n x_{ni} = \alpha_0 \tag{1}$$

where n is an integer, α_n is a constant, and x_{ni} the ith observation on the nth explanatory variable. Thus

$$x_{mi} = \frac{\alpha_0 - \sum_{j \neq m} \alpha_{ji} x_{ji}}{\alpha_m} \tag{2}$$

When Eq.2 is valid, there is multicollinearity among explanatory variables.

The principal component analysis is one method to overcome the multicollinearity problem. For an $n \times p$ matrix：

$$X = \begin{pmatrix} x_{11} & x_{12} & \Lambda & x_{1p} \\ x_{21} & x_{22} & \Lambda & x_{2p} \\ \Lambda & \Lambda & \Lambda & \Lambda \\ x_{n1} & x_{n2} & \Lambda & x_{np} \end{pmatrix} \tag{3}$$

Its correlation coefficient can be calculated by

$$r_{ij} = \frac{\sum_{k=1}^{n} (x_{ki} - \bar{x}_i)(x_{kj} - \bar{x}_j)}{\sqrt{\sum_{k=1}^{n} (x_{ki} - \bar{x}_i)^2} \sqrt{\sum_{k=1}^{n} (x_{kj} - \bar{x}_j)^2}} \tag{4}$$

And, the matrix of correlation coefficient is

$$R = \begin{pmatrix} r_{11} & r_{12} & \Lambda & r_{1p} \\ r_{21} & r_{22} & \Lambda & r_{2p} \\ \Lambda & \Lambda & \Lambda & \Lambda \\ r_{n1} & r_{n2} & \Lambda & r_{np} \end{pmatrix} \tag{5}$$

Let

$$\begin{vmatrix} r_{11} - \lambda & r_{12} & \Lambda & r_{1p} \\ r_{21} & r_{22} - \lambda & \Lambda & r_{2p} \\ \Lambda & \Lambda & \Lambda & \Lambda \\ r_{n1} & r_{n2} & \Lambda & r_{np} - \lambda \end{vmatrix} = 0 \tag{6}$$

Eigenvalues λ_i(i=1,2,…,n) and eigenvectorsγ_i=(γ_{i1},γ_{i1}, …,γ_{ip}) can be obtained by solving Eq.6. let $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_n$. The ith principal component can be written as

$$Y_i = \gamma_{i1} z_1 + \gamma_{i2} z_2 + \Lambda + \gamma_{ip} z_p \tag{7}$$

and its variance is

$$\beta_k = \frac{\lambda_k}{\sum_{i=1}^{n} \lambda_i} \tag{8}$$

The cumulative variance is

$$\sum_{j-1}^{k} \beta_j = \frac{\sum_{j-1}^{k} \lambda_j}{\sum_{i=1}^{n} \lambda_i} \tag{9}$$

The load is

$$l_{ij} = \sqrt{\lambda_i} \gamma_{ij} \tag{10}$$

The component scores for all principal components are

$$\begin{cases} z_1 = l_{11}x_1 + l_{12}x_2 + \Lambda + l_{1p}x_p \\ z_2 = l_{21}x_1 + l_{22}x_2 + \Lambda + l_{2p}x_p \\ \Lambda \\ z_n = l_{n1}x_1 + \ln_{22} x_2 + \Lambda + n_{2p}x_p \end{cases} \tag{11}$$

Results

One can note that principal component analysis is the same for the same input data if input data are not cleaned [49]. To increase interpretability and void the multicollinearity problem by using principal component analysis in the input data-oriented a target, a personalized optimization will be first performed. In other words, the input data will be firstly filtered based on its correlation with the target data. In this article, the correlation coefficient between the input data and target data will be calculated according to Eq.4. After the input data that is not significantly correlated to the target data (p>0.01) have been removed, the principal component analysis will be performed for the selected input data. Finally, the multivariate regression method has been used to justify the relationship between the principal components and the target data. In this article, we do focus on the whole authors in China, whole journals published by China not focus on special types of authors in china. In other

words, the study by using the cites in the Web of science or ORCID to narrow down a list of authors could be a future job.

Table 1 shows the data (1996-2018) of Life expectancy at birth, Death rate, School enrolment (primary), School enrollment (tertiary), Current health expenditure per capita, Adjusted net national income per capita, Adjusted savings: education expenditure, intellectual properties, and Nurses and midwives in China. Because the above data have different scales and units, normalization (Z-score) have first been performed before applications of statistics because it can adjust values measured on different scales to a notionally common scale [36-42]. Life expectancy at birth in China is found to nearly linearly increase with time since 1996, which is shown in Figure 1. Figure 1 also illustrates that Death rate, School enrolment (primary), School enrollment (tertiary), Current health expenditure per capita, Adjusted net national income per capita, Adjusted savings: education expenditure, intellectual properties, and Nurses and midwives in China are found to fluctuate but has a growth trend. School enrolment (primary) is found to fluctuate. In this article, either the Life expectancy at birth or the Death rate is used to measure health and well-being in China.

Table 1 Life expectancy at birth, Death rate, School enrolment (primary), School enrollment (tertiary), Current health expenditure per capita, Adjusted net national income per capita, Adjusted savings: education expenditure, intellectual properties, and Nurses and midwives in China. The data come from the website of the World Bank (https://data.worldbank.org).

Year	Life expectancy at birth, total (years)	Death rate, crude (per 1,000 people)	School enrollment, primary (% gross)	School enrollment, tertiary (% gross)	Current health expenditure per capita (current US$)	Adjusted net national income per capita (constant 2010 US$)	Adjusted savings: education expenditure (current US$)	Nurses and midwives (per 1,000 people)
2018	76.704	7.1	100.2228	50.60444	..	5862.628	2.43E+11	..
2017	76.47	7.11	99.40481	49.07326	440.8256	5405.507	2.17E+11	2.6621
2016	76.21	7.09	97.96192	48.01902	398.3316	5161.977	1.99E+11	2.4665
2015	75.928	7.11	96.3186	46.04043	392.846	4837.549	1.96E+11	2.2914
2014	75.629	7.16	95.79643	42.43073	361.7244	4474.737	1.87E+11	2.1349
2013	75.321	7.16	99.5646	32.43367	328.1849	4112.281	1.7E+11	1.9886
2012	75.013	7.15	99.7911	28.72567	283.5222	3834.553	1.52E+11	1.7938
2011	74.708	7.14	99.04702	25.64785	237.9336	3519.379	1.34E+11	1.6213
2010	74.409	7.11	98.96422	24.19849	187.7335	3362.863	1.08E+11	1.4881
2009	74.119	7.08	100.0061	22.44306	163.7122	3088.494	9.12E+10	1.3552
2008	73.835	7.06	100.7424	20.68412	132.7853	2740.451	8.27E+10	1.233
2007	73.553	6.93	100.7071	20.52122	97.74693	2596.522	6.37E+10	1.1518
2006	73.271	6.81	100.9933	20.21919	81.79035	2284.692	4.92E+10	1.0599
2005	72.985	6.51	..	19.087	72.36211	2022.022	4.06E+10	1.0086
2004	72.689	6.42	..	17.69126	63.699	1806.959	3.49E+10	0.9836
2003	72.381	6.4	..	15.45268	56.03277	1648.989	2.95E+10	0.9573
2002	72.061	6.41	..	12.62848	49.4711	1492.254	2.61E+10	0.9483
2001	71.732	6.43	112.3416	9.78911	43.94076	1345.958	2.36E+10	1.083
2000	71.397	6.45	..	7.59041	42.35368	1223.285	2.14E+10	0.9763
1999	71.063	6.46	..	6.39428	..	1133.511	1.93E+10	0.9662
1998	70.737	6.5	105.7694	5.86393	..	1052.53	2.03E+10	0.9531
1997	70.428	6.51	105.5071	5.35011	..	978.5956	1.94E+10	0.9445
1996	70.14	6.56	108.0742	4.91532	..	904.9024	1.45E+10	0.924

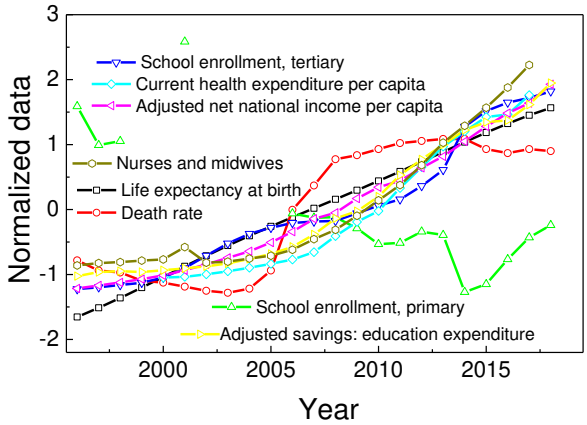

Fig. 1 Normalized Life expectancy at birth, Death rate, School enrolment (primary), School enrollment (tertiary), Current health expenditure per capita, Adjusted net national income per capita, Adjusted savings: education expenditure, intellectual properties, and Nurses and midwives in China as a function of time. The raw data come from the website of the World Bank (https://data.worldbank.org).

Table 2 shows the data (1996-2019) of Documents and its citation situation, International Collaboration articles, open access articles, journals, and open access journals published by China. Figure 2 shows that only the number open access articles in China are found to monotonous increases with time since 1996, whereas Documents and its citation situation, International Collaboration articles, journals, and open access journals published by China are found to fluctuates.

Table 2 Documents and its citation situation, International Collaboration articles, open access articles, journals, and open access journals published by China. The data come from the website of SCImago (https://www.scimagojr.com).

Year	Documents	Cited documents	Cites	External Cites	International Collaboration	Open Access	Journals	Open access journals
2019	684048	199074	544310	164545	162050	182982	662	77
2018	605616	378798	2161615	681294	140381	155037	682	80
2017	538162	393539	3512243	1209703	120602	132280	683	76
2016	498325	382165	4308362	1569550	107339	107090	682	77
2015	460425	361010	4987119	1909799	95584	90105	648	67
2014	490859	353627	5257180	2093561	86391	74855	635	57
2013	456542	324831	5145005	2138702	76196	64235	626	51
2012	415082	296107	4913231	2124347	65084	47028	595	41
2011	393879	273191	4548474	2000236	57939	35724	612	37
2010	344017	246625	4229403	1917681	50295	23977	605	33
2009	308460	224807	3895162	1794314	44109	20173	595	27
2008	261264	194182	3419775	1587921	37961	15806	577	23
2007	223247	166440	2961272	1365609	32326	13193	538	21
2006	201159	147615	2550868	1186712	28222	11325	565	21
2005	171226	124369	2194990	1032205	23663	7756	537	16
2004	117131	89148	1752095	853695	19279	4907	501	14
2003	81740	62404	1303917	650898	15203	3261	473	13
2002	68633	51546	998871	495375	11049	2148	449	13
2001	65674	45734	794033	398386	8774	1648	449	12
2000	51443	36599	636868	326461	8364	1358	375	12
1999	43315	29580	495957	267703	6839	1030	367	11
1998	42555	26791	411332	228716	6736	1055		
1997	36113	22884	353338	207839	6088	743		
1996	30780	18698	282718	164565	5331	634		

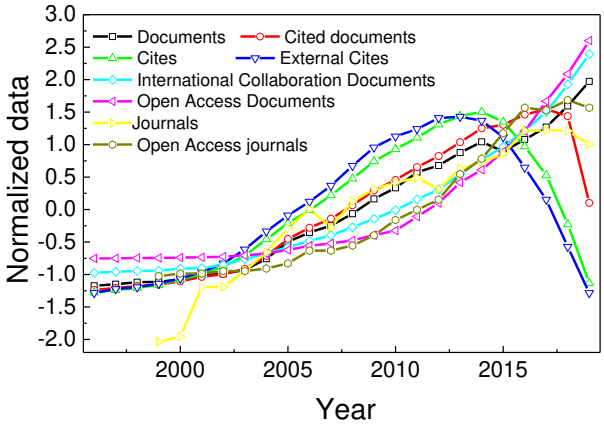

Fig. 2 Normalized Documents and its citation situation, International Collaboration articles, open access articles, journals, and open access journals published by China as a function of time. The raw data come from the website of t the website of SCImago (https://www.scimagojr.com).

Table 3 shows the Pearson correlation coefficient *r*. Life expectancy at birth, total (years) has a significant very strong positive linear relationship with Cited documents ($r(21)=0.981$, $p<0.01$), Adjusted net national income per capita (constant 2010 US$) ($r(21)=0.979$, $p<0.01$), Documents ($r(21)=0.977$, $p<0.01$), Journals ($r(18)=0.971$, $p<0.01$), School enrollment at tertiary education (% gross) ($r(21)=0.964$, $p<0.01$), Current health expenditure per capita (current US$) ($r(16)=0.964$, $p<0.01$), Adjusted savings: education expenditure (current US$) ($r(21)=0.95$, $p<0.01$), Open Access journals ($r(18)=0.943$, $p<0.01$), International Collaboration Documents ($r(21)=0.94$, $p<0.01$), Nurses and midwives (per 1,000 people) ($r(20)=0.898$, $p<0.01$), Open Access Documents($r(21)=0.861$, $p<0.01$), and Cites ($r(21)=0.858$, $p<0.01$). Life expectancy at birth, total (years) has a significant strong positive linear relationship with External Cites ($r(21)=0.778$, $p<0.01$). Life expectancy at birth, total (years) has a significant very strong negative linear relationship with School enrollment at primary education (% gross) ($r(21)=-0.824$, $p<0.01$).

Death rate, crude (per 1,000 people) has a significant very strong positive linear relationship with Cited documents ($r(21)=0.916$, $p<0.01$), Documents ($r(21)=0.911$, $p<0.01$), Cites ($r(21)=0.907$, $p<0.01$) , Journals ($r(18)=0.879$, $p<0.01$), Adjusted net national income per capita (constant 2010 US$) ($r(21)=0.868$, $p<0.01$), External Cites ($r(21)=0.866$, $p<0.01$), Adjusted savings: education expenditure (current US$) ($r(21)=0.986$, $p<0.01$), International Collaboration Documents ($r(21)=0.808$, $p<0.01$), and Current health expenditure per capita (current US$) ($r(16)=0.800$, $p<0.01$). Death rate, crude (per 1,000 people) has a significant strong positive linear relationship with School enrollment at tertiary education (% gross) ($r(21)=0.793$ $p<0.01$), Nurses and midwives (per 1,000 people) ($r(20)=0.793$, $p<0.01$), Open Access Documents($r(21)=0.752$, $p<0.01$), and Open Access Documents($r(21)=0.694$, $p<0.01$).

Death rate, crude (per 1,000 people) has a significant very strong positive linear relationship with School enrollment at primary education (% gross) ($r(21)=-0.912$, $p<0.01$).

Table 3: The output for the Pearson correlation coefficient (r). The raw data come from the website of the World Bank (https://data.worldbank.org) and the website of SCImago (https://www.scimagojr.com).

Variables	Life expectancy at birth, total (years)		Death rate, crude (per 1,000 people)	
	r	Sig.	*r*	Sig.
School enrollment, primary (% gross)	-0.824	0.000	-0.912	0.000
School enrollment, tertiary (% gross)	0.964	0.000	0.793	0.000
Current health expenditure per capita (current US$)	0.964	0.000	0.8	0.000
Adjusted net national income per capita (constant 2010 US$)	0.979	0.000	0.868	0.000
Adjusted savings: education expenditure (current US$)	0.95	0.000	0.86	0.000
Nurses and midwives (per 1,000 people)	0.898	0.000	0.793	0.000
Documents	0.977	0.000	0.911	0.000
Cited documents	0.981	0.000	0.916	0.000
Cites	0.858	0.000	0.907	0.000
External Cites	0.778	0.000	0.866	0.000
International Collaboration Documents	0.94	0.000	0.808	0.000
Open Access Documents	0.861	0.000	0.694	0.000
Journals	0.971	0.000	0.879	0.000
Open Access journals	0.943	0.000	0.752	0.000

The above collected multidimensional data is likely to be related, in other words, the collected multidimensional data have commonness. To see the utility of various kinds of collected multidimensional information data, it is obvious that this commonness should be removed. However, we can not roughly remove the relevant information data, because the reduction of relevant information data will inevitably lose a lot of important information, which leads to the existence of no one in the effectiveness and reliability of the target information. Besides, how to simply process these multi-dimensional collected information data into single-dimensional collected information data, then the result of calculating the target information must be independent. Therefore, there is no way to compare the comprehensive conclusion of multidimensional information collection (input information) with the information collected (input information) of each dimension. Factor analysis is a technology to extract common factors from variable groups. It is just right for solving the above problems.

Table 4 shows the principal component analysis results of eigenvalues, individual, and cumulative. According to statistics, the principle components have been defined as those eigenvalues that are larger than 1 [36-42]. In the following, only principle components that are larger than 1 have been discussed. Table 4 demonstrates that two principal components whose eigenvalues are larger than 1. The first principal component accounts for 85.6% of the

total variance. And the second principal component accounts for 11.8% of the total variance. Both principal components account for 97.3% of the total variance. One can note that each principal component is composed of 14 types of input data including education, income, scholarly publishing, etc. and there are two principal components. Such results imply that there will be a complicated relationship between the input data and the target data even there is a simple linear relation between the principal components and the target data. At the same time, the input data of documents, education expenditure, journals, etc. are treated as the data of knowledge services. In other words, the data of knowledge services have a complicated dependent relation with public health. Such conclusions agree well that both the provision of education and good governance and the spread of values, beliefs, and institutions are important to regional development with a complex interplay between technological, social, and geographical factors and a difficult to measure the knowledge services [35, 50].

Table 4 Eigenvalues, individual and cumulative by using the normalized data. The raw data come from the website of the World Bank (https://data.worldbank.org) and the website of SCImago (https://www.scimagojr.com).

Components	Eigenvalue	Individual, %	Cumulative, %
1	11.981	85.576	85.576
2	1.648	11.769	97.345
3	.267	1.908	99.253
4	.071	.505	99.758
5	.020	.144	99.902
6	.006	.043	99.945
7	.003	.024	99.969
8	.002	.015	99.984
9	.002	.011	99.995
10	.000	.003	99.999
11	.000	.001	100.000
12	2.651E-5	.000	100.000
13	2.737E-16	1.955E-15	100.000
14	-2.107E-16	-1.505E-15	100.000

Table 5 demonstrates the principal component analysis results of loading. Loadings indicate the importance of the original variables in the formation of new variables[36-42]. The order from the largest loading to the smallest loading for the first principal component is Open Access Documents, Nurses and midwives (per 1,000 people), Open Access journals, International Collaboration Documents, School enrollment, tertiary (% gross), Current health expenditure per capita (current US$), Adjusted net national income per capita (constant 2010 US$), Adjusted savings: education expenditure (current US$), Cited documents, Documents, Journals, Cites, External Cites, and School enrollment, primary (% gross). The order from the largest loading to the smallest loading for the second principal component is Cites, Documents, Journals, Cited documents, Adjusted savings: education expenditure (current

US$), Adjusted net national income per capita (constant 2010 US$), Current health expenditure, per capita (current US$), International Collaboration Documents, School enrollment, tertiary (% gross), Open Access journals, Nurses and midwives (per 1,000 people), Open Access Documents, and School enrollment, primary (% gross). Obviously, Open Access Documents is the largest loading in the first principal component, and Cites is the largest loading in the second principal component. School enrollment at primary education is the smallest loading for both principal components.

Table 5 The loadings after varimax rotation by using the normalized data. The raw data come from the website of the World Bank (https://data.worldbank.org) and the website of SCImago (https://www.scimagojr.com).

Variables	**The first principal component**	**The second principal component**
School enrollment, primary (% gross)	-.421	-.833
School enrollment, tertiary (% gross)	.934	.310
Current health expenditure per capita (current US$)	.916	.379
Adjusted net national income per capita (constant 2010 US$)	.898	.435
Adjusted savings: education expenditure (current US$)	.886	.446
Nurses and midwives (per 1,000 people)	.965	.237
Documents	.809	.574
Cited documents	.836	.547
Cites	.388	.908
External Cites	.109	.982
International Collaboration Documents	.946	.323
Open Access Documents	.989	.140
Journals	.781	.556
Open Access journals	.961	.259

The load of education expenditure that is 0.886 in the first principal components is very high. It can be compared with that of Current health expenditure per capita (0.916) and net national income per capita (0.898). That the level of education seems to exert a very high impact on regional growth has been concluded [51]. It has been found that there is a significant relationship between regional growth and higher education within North European countries [52]. A high load of education expenditure in the principal analysis agrees well with those conclusions drawn in the references [51,52]. At the same time, it was found that school-based programs to promote health knowledge in an area characterized by low levels of income and education may have much smaller payoffs than programs that encourage the investments in time preference made by the more educated [12]. Such a viewpoint can be partly supported by the load education expenditure locate the middle of all 14 factors because it ranks eighth out of 14 factors. Significant non-monetary returns to education concerning health outcomes and not necessarily for health-related behavior have been found [13]. Schooling could be an important factor influencing nonmarket production processes

associated with fertility and child health [53]. These loads that are shown in Table 5 support the above findings on health promotion in references [12,13,53]. Most loads of the number of documents and journals indexed by SCImago are comparable with those of education expenditure, Current health expenditure per capita, and Nurses and midwives. It agrees well with the conclusion that knowledge plays a crucial role in the process of economic development [54]. That the information and knowledge exercise a decisive impact on the functionality and performance of organizations, assuring the sustainability of the economy in the long term has been found at the global level [5]. And increasing knowledge and developing knowledge can improve public health, for example, increasing knowledge and awareness by training health professionals to communicate and deliver targeted preconception care interventions may be important [9]; it is necessary to develop sustainable strategies for collective health-promoting activities, in addition to strengthening multidisciplinary work and Continuing Education actions [10]. All the above conclusions demonstrate that education, income, knowledge, etc. can have an impact on public health. Most loads that are shown in Table 5 are comparable (loads of 11 input variables change from 0.78 to 0.99). It means that all factors can not be neglected for public health promotion.

The component score coefficient matrix is an output product in the principal components analysis [36-42]. The component score coefficient represents the weighting of variables to be used when computing the saved variables of the components. Table 6 shows the principal component analysis results of the component score coefficient. The order from the largest component score coefficient to the smallest loading for the first principal component is Open Access Documents, Nurses and midwives (per 1,000 people), Open Access journals, School enrollment, tertiary (% gross), International Collaboration Documents, Current health expenditure per capita (current US$), School enrollment, primary (% gross), Adjusted net national income per capita (constant 2010 US$), Adjusted savings: education expenditure (current US$), Cited documents, Documents, Journals, Cites, and External Cites. The order from the largest component score coefficient to the smallest loading for the second principal component is External Cites, Cites, Documents, Journals, Cited documents, Adjusted savings: education expenditure (current US$), Adjusted net national income per capita (constant 2010 US$), Current health expenditure per capita (current US$), International Collaboration Documents, School enrollment, tertiary (% gross), Open Access journals, Nurses and midwives (per 1,000 people), Open Access Documents, and School enrollment, primary (% gross).

Table 6 Component score coefficient matrix by using the normalized data. The raw data come from the website of the World Bank (https://data.worldbank.org) and the website of SCImago (https://www.scimagojr.com).

Variables	**The first principal component**	**The second principal component**
School enrollment, primary (% gross)	.099	-.298
School enrollment, tertiary (% gross)	.132	-.067
Current health expenditure per capita (current US$)	.113	-.030
Adjusted net national income per capita (constant 2010 US$)	.096	.000
Adjusted savings: education expenditure (current US$)	.091	.008
Nurses and midwives (per 1,000 people)	.156	-.108
Documents	.045	.086
Cited documents	.057	.068
Cites	-.123	.340
External Cites	-.201	.439
International Collaboration Documents	.132	-.063
Open Access Documents	.183	-.160
Journals	.043	.084
Open Access journals	.150	-.097

The component score coefficients of education expenditure, School enrollment, tertiary (% gross), Current health expenditure per capita (current US$), and Nurses and midwives in the first and second principal components are also very high. Most component score coefficients (9 input variables) vary from 0.09 to 0.18. In these 9 variables, there are factors for education, net national income per capita, scholarly publishing, etc. It further supports that the level of education exerts a very high impact on regional growth [51] and there is a significant relationship between regional growth and higher education [52]. These results also agree well with that school-based programs to promote health knowledge in an area characterized by low levels of income and education may have a small payoff [12], there are Significant non-monetary returns to education concerning health outcomes [13], schooling could be an important factor influencing fertility and child health [53]. Most component score coefficients of the Document and journals published in China are comparable with those of education expenditure, School enrollment, tertiary (% gross), Current health expenditure per capita (current US$), and Nurses and midwives. This might be because knowledge is the most powerful engine for economic development [54], accelerated sustainable economic growth [5], increasing knowledge, and developing knowledge can improve public health [9,10]. That all these input factors can improve health and well-being according to Table 6 is consistent with the above conclusion drawn in the literature.

Discussion

According to Table 1 out of 14 components, only these factors whose eigenvalues are larger than 1 have been selected for multiple linear regressions between Life expectancy at birth or Death rate and the principal components.

Table 7 demonstrates the results of multivariate multiple linear regression analysis results based on principal component scores. 71.3 % of the variation in the normalized Life expectancy at birth of China could be explained by the first principal component, which is determined from the stepwise regression analysis. 99.3 % of the variation in the normalized Life expectancy at birth of China could be explained by both the first and second principal components. The above results reveal that the first principal component gives the most contribution to the normalized Life expectancy at birth of China. 15.8 % of the variation in the normalized Death rate of China could be explained by the first principal component, which is determined from the stepwise regression analysis. 92.8 % of the variation in the normalized Death rate of China could be explained by both the first and second principal components. The above results reveal that the second principal component gives the most contribution to the normalized Death rate of China. In other words, the selected data might be enough to explain the Life expectancy at birth of China, but should be not enough to explain the death rate of China.

Table 7: Multivariate multiple linear regression analysis results. The raw data come from the website of the World Bank (https://data.worldbank.org) and the website of SCImago (https://www.scimagojr.com).

	Before stepwise regression analysis						
	Variable	**Unstandardized Coefficients**		**Standardized coefficients**	**t**	**Sig.**	**R^2**
		B	**Standard Error**	**β**			
	Intercept	.549	.017		32.366	.000	.993
Life expectancy at birth, total (years)	**PC1**	.555	.018	.845	31.466	.000	
	PC2	.348	.018	.529	19.696	.000	
	After stepwise regression analysis						
	Intercept	.549	.102		5.381	.000	.713
	PC1	.555	.106	.845	5.232	.000	
Death rate, crude (per 1,000 people)	**Before stepwise regression analysis**						
	Intercept	.669	.052		12.878	.000	.928
	PC1	.254	.054	.397	4.688	.001	
	PC2	.561	.054	.878	10.368	.000	
	After stepwise regression analysis						
	Intercept	.669	.170		3.940	.002	.158
	PC1	.254	.177	.397	1.435	.179	

These linear relationships between the principal components and the normalized Life expectancy at birth or Death rate of China demonstrate that public health has a dependent relationship on the principal components. Every principal component is composed of 14 input variables. Most variables have a similar contribution to the principal components. It means that some factors of scholarly publishing, education, income, health expenditure, etc. have a similar contribution to new variables that have been obtained by using the principal component analysis. These linear relationships between the principal components (it includes scholarly publishing, education, income, health expenditure, etc.) and the target data (the data of public health in China) support the well-known conclusions that education can exert a very high impact on regional growth [51,52], and an impact on health promotion[12,13,53]. Such linear relationships between the principal components (it includes scholarly publishing, education, income, health expenditure, etc.) and the target data (the data of public health in China) could originate that knowledge is necessary for the health benefits and the knowledge for health and well-being is various [6], either increasing knowledge or developing knowledge can improve public health [9,10], lack of knowledge can cause serious health problems [11], it needs knowledge for making proper decisions and realizing actions [5], making better health decisions leads to improved health outcomes [13], knowledge is the most powerful engine for economic development [54], knowledge can accelerate sustainable economic growth [5]. In other words, both economic development and regional development can improve health and well-being.

The public health and well-being in China are measured by Life expectancy at birth and Death rate. Tables 1-7 show that the data of Life expectancy at birth or Death rate of China are strong linear dependent on the principal components. Each principal component is composed of the input data related to education, income, and scholarly publishing, etc. Hence, the linear relationships between the principal components including the factors such as scholarly publishing, education, income, health expenditure, etc.) and the data of public health in China imply that there is a strong interdependence between scholarly publishing and public health in China. Scholarly publishing plays a similar role in public health, which has a similar behavior of education, income, health expenditure, etc. The results shown in Tables 1-7 are new. The very good linear relationship between the principal components and the Life expectancy at birth or Death rate of China could result from the well-known conclusions that knowledge is necessary for the health benefits and the knowledge for health and well-being is various [6], either increasing knowledge or developing knowledge can improve public health [9,10], lack of knowledge can cause serious health problems [11], it needs knowledge for

making proper decisions and realizing actions [5], making better health decisions leads to improved health outcomes [13].

Conclusions

One can note that the combination method is proposed in this article is not the actual answer. Instead, this model is an example of showing our idea to study the relationship between the input data (knowledge, education, etc.) and the target data (public health). Besides, due to the limited or possible error of the collected data of knowledge, education, etc., the relationship the input data (knowledge, education, etc.) and the target data (public health) based on the proposed method in this paper may be different from the actual situation. However, the proposed method can be used to study the issue of how the target data depends on the input data. This is because the proposed method provides a new idea for the influence of knowledge in future studies.

The proposed method can be treated as a new method introduced to study the correlation between scholarly publishing and health and well-being.

Principal component analysis has been used to avoid the multicollinearity problem in the data used in this article. Through a case study of the data of health and well-being, education, income, and knowledge translation of scholarly publishing in China, explore the effects of the various activities of scholarly publishing on health and well-being. Results obtained from the principal analysis show that two principal components whose eigenvalues are larger than 1. The first principal component accounts for 85.6% of the total variance. And the second principal component accounts for 11.8% of the total variance. Both principal components account for 97.3% of the total variance. It implies that only the first and the second principal components at the most needed to be considered. Multivariate multiple linear regression analysis based on principal component analysis demonstrates that 71.3 % of the variation in the normalized Life expectancy at birth of China could be explained by the first principal component, which is determined from the stepwise regression analysis. On the other hand, 99.3 % of the variation in the normalized Life expectancy at birth of China could be explained by both the first and second principal components. The contribution of the education, the income, and the scholarly publishing to the first principal component can not be neglected. This implies that scholarly publishing especially on open access publishing could be an important factor in improving health and well-being. All results demonstrate that scholarly publishing can give an important contribution to the health and well-being of China. The findings in this paper agree with the former conclusions reported in the literature that that

various knowledge is necessary for health and well-being [6], knowledge can promote public health [9,10], serious health problems could occur due to lack of knowledge can cause [11], knowledge is necessary for making proper decisions and realizing actions [5], health outcomes can be improved by making better health decisions [13]. In conclusion, the combination of the correlation analysis, the principal component analysis, and multivariate regression methods is valid in the study of the correlation between scholarly publishing and health and well-being.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The datasets generated and/or analysed during the current study are available in the website of the World Bank (https://data.worldbank.org) and the website of SCImago (https://www.scimagojr.com).

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Na analyzed and interpreted the data, and wrote the manuscript. All authors read and approved the final manuscript.

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Table

Table 1 Life expectancy at birth, Death rate, School enrolment (primary), School enrollment (tertiary), Current health expenditure per capita, Adjusted net national income per capita, Adjusted savings: education expenditure, intellectual properties, and Nurses and midwives in China. The data come from the website of the World Bank (https://data.worldbank.org).

Table 2 Documents and its citation situation, International Collaboration articles, open access articles, journals, and open access journals published by China. The data come from the website of SCImago (https://www.scimagojr.com).

Table 3: The output for the Pearson correlation coefficient (*r*). The raw data come from the website of the World Bank (https://data.worldbank.org) and the website of SCImago (https://www.scimagojr.com).

Table 4 Eigenvalues, individual and cumulative by using the normalized data. The raw data come from the website of the World Bank (https://data.worldbank.org) and the website of SCImago (https://www.scimagojr.com).

Table 5 The loadings after varimax rotation by using the normalized data. The raw data come from the website of the World Bank (https://data.worldbank.org) and the website of SCImago (https://www.scimagojr.com).

Table 6 Component score coefficient matrix by using the normalized data. The raw data come from the website of the World Bank (https://data.worldbank.org) and the website of SCImago (https://www.scimagojr.com).

Table 7: Multivariate multiple linear regression analysis results. The raw data come from the website of the World Bank (https://data.worldbank.org) and the website of SCImago (https://www.scimagojr.com).

Captions

Fig. 1 Normalized Life expectancy at birth, Death rate, School enrolment (primary), School enrollment (tertiary), Current health expenditure per capita, Adjusted net national income per capita, Adjusted savings: education expenditure, intellectual properties, and Nurses and midwives in China as a function of time. The raw data come from the website of the World Bank (https://data.worldbank.org).

Fig. 2 Normalized Documents and its citation situation, International Collaboration articles, open access articles, journals, and open access journals published by China as a function of time. The raw data come from the website of SCImago (https://www.scimagojr.com).

Figures

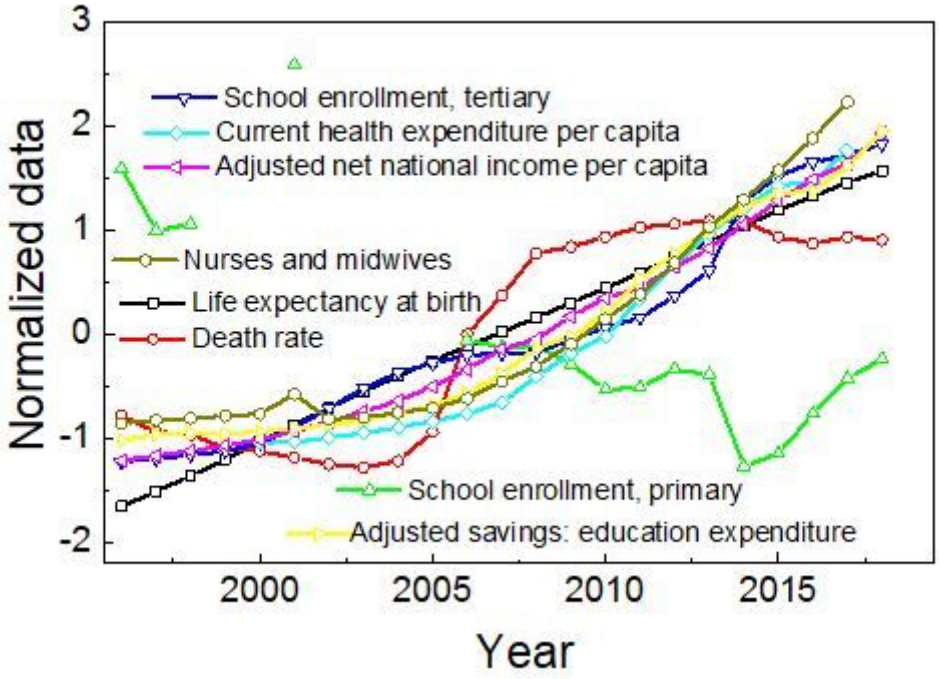

Figure 1

Normalized Life expectancy at birth, Death rate, School enrolment (primary), School enrollment (tertiary), Current health expenditure per capita, Adjusted net national income per capita, Adjusted savings: education expenditure, intellectual properties, and Nurses and midwives in China as a function of time. The raw data come from the website of the World Bank (https://data.worldbank.org).

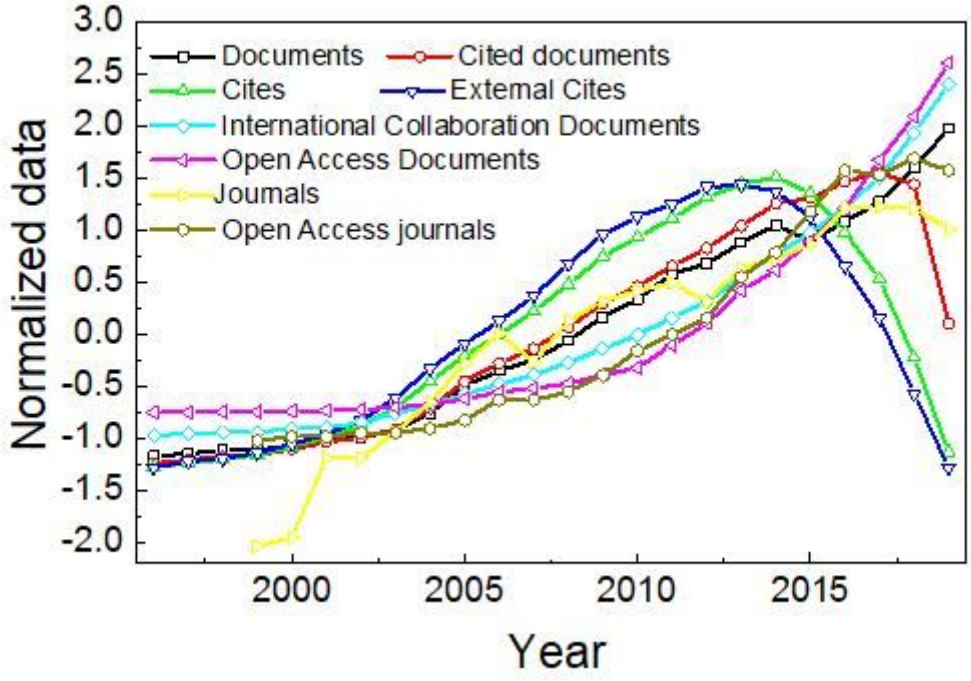

Figure 2

Normalized Documents and its citation situation, International Collaboration articles, open access articles, journals, and open access journals published by China as a function of time. The raw data come from the website of t the website of SCImago (https://www.scimagojr.com).