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Advances in Health and Behavior

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EDITORIAL

Behavior as the dynamic unit between polar opposites − Health and Disease

Editor-in-Chief: Alba Malara

The current definition of health of the World Health Organization (WHO), formulated in 1948, describes health as "*a state of complete physical, mental and social well-being and not simply the absence of disease or infirmity*".[1] Although, this formulation was been revolutionary because it overcame the negative definition of health as the absence of disease and included physical, mental and social domains, it has been partially criticized over the past 60 years. This definition is in fact referred to the disease acute pattern, which is transient and limited in the time. Today, the number of people living with chronic diseases for decades is increasing worldwide. Ageing with chronic diseases has become the norm representing the main care burden and the most of the expenditures of the healthcare system. In this context the WHO definition becomes confounding as it could declare people with chronic diseases definitively ill. Machteld Huber, *et al*. believe that the WHO would benefit if it extends the definition of health, taking into account that the demography of populations and the nature of disease have changed considerably since 1948.[2] Georges Canguilhem suggested a new idea of health as a capability to adapt and self-manage in the social, physical and emotional challenges, it moving from the static formulation towards a more dynamic one based on the resilience or capacity to cope and maintain and restore ones integrity, equilibrium, and sense of well-being.[3] Health, considered as "*ability to adapt*", becomes a condition of equilibrium (dynamic, therefore always new, continually to be reset) between the subject and the environment (human, physical, biological, social) that surrounds it. Therefore, health and disease cannot be simply defined in dichotomous terms, present or absent; they are continually redefined as people adapt to changing functional skills across the spectrum of life. The change in the health concept makes medical care that focuses only on the diagnosis and treatment of individual diseases no longer applicable to new paradigms of biological and clinical complexity. The current approach to consider disease as a result of individual organ impairments is very useful, but it fails in understanding the whole system, its complexity, environmental adaptability and overall health of the human organism. Clinical management, primarily oriented to disease, can inadvertently lead to underestimate overburden or abuse of treatment.[4] The 21st century clinician has to consider the individual, both healthy and ill, as the complex system that it really is, structured on systems, organs, tissues and cells, in which the individual parts that compose it interact with each other (physiologically and physiopathologically) in a dynamic way with non-biological determinants, in order to realize a comprehensive functional system.[5] It is necessary to produce a synthesis that respects the singularity of the patient with its complexity defined by the genotypic and phenotypic diversity, and by the dynamic interweaving between clinical (disease − specific) and non-clinical determinants (genetic aspects including the gene-environment interaction, environmental factors, socio-family status, economic status, psychological features, *etc*.), and finally by the availability and accessibility to care services. The complex framework that today characterizes the concept of health cannot be approached only according to the methodology of Evidence-Based Medicine (EBM). By its nature, the EBM researches and obtains evidence related to diseases with a well-defined ontological definition, by clinical trials focused as much as possible on patients with a specific disease but without other relevant clinical conditions that would be "*confusing*" for the researched evidence. While the EBM provides for a "*chain of exclusions*" process, the methodology of complexity requires the ability to "*include*" all the different relevant elements, which contribute to a com-

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plete and real clinical picture. In this context, behavior has a broad and central role: behavioral interventions can be effective to empower health, prevent new diseases, improve the management of existing diseases, enhance quality of life and reduce health costs.[6] The benefits of behavioral interventions go beyond the impact on a particular disease or risk factor, they can influence the course and outcome of chronic diseases, defined by the WHO in the new meaning of Non-Communicable Diseases (NCDs). According to the latest Global Report on NCDs, published by WHO in 2014 and updated in 2017, 38 million deaths due to NCDs were recorded in 2012, over 40% were premature as they affected people aged less than 70 years. WHO Member States have agreed on a set of nine voluntary global objectives to be achieved by 2025: reduce the harmful use of alcohol, stop tobacco smoking habit, increase physical activity, limit salt/sodium intake, manage hypertension, block the increase of diabetes and obesity, improve treatment coverage for the prevention of heart attacks and strokes, and improve the availability and affordability of technologies and drugs essential for NCD management.[7] Changing individual behavior is very important for addressing NCDs and preventing premature deaths due to them, so we now have an unprecedented opportunity to change the course of the NCD epidemic through health behaviors. A greater recognition of the behaviors as health determinants is essential for the improvement of global health; in this field, the research moves forward thanks to the effort of many disciplines contributing to the knowledge of health and behavior. These include not only the behavioral sciences but even other relevant sciences such as neuroanatomy, neurology, neurochemistry, endocrinology, immunology, psychology, psychiatry, epidemiology, sociology and anthropology, as well as new interdisciplinary fields such as behavioral genetics, psychoneuroimmunology and behavioral medicine.

It is fundamental to increase and support research on the role of health behaviors in the prevention and treatment of chronic diseases, and at the same time propose educational and training activities for a full understanding of the interaction between health, disease and behavior.

References

[1] Constitution of the world health organization.World Health Organization, 2006. www.who.int/governance/eb/who_constitution_en.pdf.

[2] Huber M, Knottnerus JA, Green L, *et al*. How should we define health? *British Medical Journal*, 2011, **26**(343):d4163. https://doi.org/10.1136/bmj.d4163

[3] Books Z. What is health? The ability to adapt. *The Lancet*. 2009 373(9666):781. https://doi.org/10.1016/S0140-6736(09)60456-6

[4] Tinetti ME, Fried T. The end of the disease era. *The American journal of medicine*, 2004, **116**(3): 179-185. https://doi.org/10.1016/j.amjmed.2003.09.031

[5] Picard M, Juster RP, Sabiston CM. Is the whole greater than the sum of the parts? Self-rated health and transdisciplinarity. *Health*, 2013, **5**(12): 24. https://doi.org/10.4236/health.2013.512A004

[6] Dekker J, Stauder A, Penedo FJ. Proposal for an update of the definition and scope of behavioral medicine. *International journal of behavioral medicine*, 2017, **24**(1): 1-4. https://doi.org/10.1007/s12529-016-9610-7

[7] Mendis S. Global status report on noncommunicable diseases 2014. World health organization, 2014. www.who.int/nmh/publications/ncd-status-report-2014/en

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RESEARCH ARTICLE

Associations between smoking cessation and depression among the population in Northwest China

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Abstract: Many studies have indicated a relationship between smoking cessation and a history of depression. However, few studies have examined the association between smoking cessation and current depression and even fewer evidence come from mainland China. The aim of this study is to determine the prevalence of smoking quitters, the correlates of successful smoking cessation, and its relationship with depressive symptoms in Northwest China. Methods: A total of 7,644 subjects who met the study's entry criteria were randomly selected from the urban areas of three provinces in Northwest China and interviewed using standardized assessment tools, including basic characteristics of households and detailed information on family members. All respondents provided informed consent. Results: people with depression symptom have a more than 1.5-fold risk of abstinence from smoking than those without depression (OR=1.54; 95% CI, 1.2 to 1.9) and the likelihood ratio test for two models reach statistical significance (x^2=13.2, p<0.001). Smoking quitters have a more than 1.5-fold risk of having depressive symptoms than current smokers (OR=1.54; 95% CI, 1.2 to 1.9) and the likelihood ratio test for two models is also statistically significant (x^2=6449.85, p<0.001). Conclusions: The prevalence of smoking quitters in urban areas of Northwest China is very low. After controlling certain confounders, smoking cessation is associated with current depressive symptoms. More rigorous surveys are needed to elucidate the barriers to smoking cessation in China. Government bodies in China should implement appropriate strategies and execute effective measures to mitigate its harmful consequences.

Keywords: smoking cessation, depression, Northwest China

1 Introduction

There are an estimated 301 million people in China who smoke tobacco. Approximately 52.9% of the men and 2.4% of the women in China smoke cigarettes,[1] which accounted for nearly one-third of the world's smokers in 2010. Cigarette smoking is one of major risk factors for mortality in China, with an estimated 673,000 deaths being attributable to smoking in 2005.[2] Most Chinese smokers know that smoking is harmful to their health and that smoking cessation can improve their health and well-being. However, smoking cessation is usually difficult. Though China's government has made numerous efforts to control tobacco use, the quit ratio among Chinese smokers remains low compared to developed countries.[3] This research aims to explore the possible barriers to successful smoking cessation from the perspective of psychology and to provide evidence-based suggestions for China's tobacco control policy.

Many studies have shown an association between smoking and depression in various settings, with the prevalence of cigarette smoking being significantly higher among people with current major depression than among the general population.[4] In U.S., data from the National Co-Morbidity Survey conducted from 1991 to 1992 indicated that 41.0% of persons with mental illness in the past month were current smokers, while the prevalence of current smoking among the entire population was just 28.5%.[5] The Composite International Diagnostic Interview conducted in Australia shows that after controlling for social-demographical confounders, current tobacco users had an odds ratio of 1.5 (CI 1.2 to 1.8) for any affective disorders and an odds ratio of 1.7 (CI 1.4 to 2.0) for any anxiety disorders.[6] By contrast, other studies have observed no significant associations between smoking and depressive symptoms.[7]

In addition, many studies have suggested that depression has been negatively associated with success-

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ful smoking cessation. A cross-sectional study using the Beck Depression Inventory found that higher depression scores were related to lower smoking cessation self-efficacy, especially among male smokers.[8] Evidence from the 2006 behavioural Risk Factor Surveillance System data in the U.S. show that unsuccessful quitters experienced more lifetime depression and anxiety than non-quitters (OR=1.2;95% CI, 1.0 to 1.4), whereas successful quitters experienced less (OR=0.7, 95% CI, 0.6 to 0.8). Current depression prevalence was 14.3% among non-quitters, 18.8% among unsuccessful quitters, and 8.0% among successful quitters.[9] Moreover, results from many longitudinal studies indicate that higher scores on depressive symptoms negatively predicted quitting success.[10] By contrast, a meta-analysis, including 15 peer reviewed papers, concluded that a lifetime history of major depression does not appear to be an independent risk factor for cessation failure,[11] and later studies confirmed this conclusion.[12] Accordingly, the association between depression and smoking cessation is inconclusive due to the mixed results of past studies.

However, while notably few studies targeting the mental risk factors of smoking abstinence were conducted in mainland China, a cross-sectional population-based survey was conducted in Beijing in 2003. Using the Composite International Diagnostic Interview (CIDI) and involving 5926 people, this survey concluded that having a psychiatric disorder was a risk factor associated with current smoking and current heavy smoking was also associated with a history of a major depressive episode.[13]

To fill this gap in the literature, we conducted a population-based survey in Northwest China that addressed the patterns of smoking and the mental health statuses of the smokers with the following purposes: (1) to investigate the number of current, former and non-smokers and the proportion of smoking cessation in the population aged 15 years and older; (2) to identify the socio-demographic factors and other correlates of successful smoking cessation; (3) to test the association between smoking cessation and symptoms of depression. This study will contribute to the following domains by: (1) elucidating the relationship between depressive symptoms and the patterns of smoking; (2) providing support for the theory that smoking cessation may induce a relapse of depression; (3) providing firm empirical evidence to shape policy making.

2 Methods

2.1 Data source and sample selection

The data of the present study pertain to a population-based cohort study initiated in October 2006 as part of the Chinese Urban Social Protection Survey. It was conducted by the School of Social Development and Public Policy at Beijing Normal University and the Provincial Civil Affairs Sector in Northwest China.

This survey was conducted in three cities (Lanzhou and Baiyin city in the Gansu province and Xining city in the Qinghai province). Within each city, a random sample was selected using three-stage cluster sampling design. In each of the three cities, 15 street units were randomly selected randomly in the first stage using the probability proportional to the sample size. Within each selected street unit, three residential neighbourhoods were selected, again using the probability proportional to the size sample size. Within each residential neighbourhood, 200 households were then selected by simple random sampling. Household representatives were surveyed in face-to-face interviews conducted in Chinese by trained professionals from local departments of Civil Affairs. The response rate was 89%, and all respondents provided informed consent. The study was approved by the institutional ethics committee, and all respondents provided informed consent.

The survey encompassed a wide range of background characteristics of households and detailed information on each household member including social-demographic characteristics (age, gender, education level and marital status), behaviour factors (cigarette smoking, alcohol consumption and physical activity), psychosocial factors (depression, life satisfaction and social support) and economic factors (*Dibao*, occupation, expenditure on health care, debts and medical insurance). The surveyed households and household respondents totalled 2,841 and 7,644, respectively.

2.2 Measures

2.2.1 Smoking status

Respondents were divided into 4 categories in terms of their smoking status: non-smokers who did not smoke cigarettes at all in either 2005 and 2006, initial smokers who did not smoke in 2005 but smoked in 2006, former smokers who smoked in 2005 but did not smoke at all in 2006 and current smokers who smoked both in 2005 and 2006.

2.2.2 Smoking cessation

Respondents, who were classified as smokers in 2005 and who, in 2006, indicated that they had not smoke cigarettes were considered to be successful is abstaining from smoking. Smoking cessation was thus defined as 0 (current smokers) and 1 (successful quitters or former smokers).

2.2.3 Depressive symptoms

The Center for Epidemiological Studies Depression Scale (CES-D),[14] Chinese edition, was used to measure the frequency of participants depressive symptoms. The total score of more than or equal to 16 was selected as the cutoff for possible mild to major depression.

2.2.4 Other covariates

The urban China social protection questionnaire included information on socio-demographic characteristics including age (15-24, 25-29, 30-34, 35-39, 40-49, 50-59, 60 years and older), gender (male, female), marital status (married, not married) and education (illiterate/primary school, junior high school, senior high school/technical secondary school, university degree or above) . Alcohol consumption was collapsed into four categories, "No" or , "1 to 2 times a week", "3 to 4 times a week" and "almost every day . Respondents also reported debt of household and medical insurance status (a yes/no dichotomized variable). The health-related factor was measured using the body mass index (BMI) ($<$19, 19-25 and $\geq$25 kg/m^2).

2.3 Statistical analysis

Group differences for categorical variables were examined using chi-square tests. In the first step, we analysed the association of smoking status (non-smoker, initial smoker, current smoker, and former smoker) and a range of variables. Here, differences among groups were compared using the chi-square test for categorical data.

In the second analysis, to perform the likelihood ratio test, we ran two models, one of which had a set of parameters (variables), and a second model that had all of the parameters from the first, plus another variable (depression). The dependent variable for both models was smoking cessation, which was a dichotomous variable indicating whether smokers had quit cigarette smoking during the time of the survey. All significant variables except depression, as described in Table 1, were entered as predictor variables. In turn, we tested a model containing those predictor variables against a model that contained the above variables plus the additional predictor variable of depression. Third, the likelihood ratio test was again run, but the dependent variable, different from the previous step, was a depressive symptom for both models. The depressive symptom is a dichotomized variable indicating that the subject had a CES-D score that was above sixteen.

In both models, current smoking was set as the reference category for calculating the odds of abstaining (coded as 1) versus current smoking (coded as 0). Without depressive symptoms was set as the reference category for calculating the odds of abstaining with depression (coded as 1) versus without depression (coded as 0). Covariates including socio-demographic characteristics (age, gender, marital status and education attainment), alcohol consumption, BMI, house debt and medical insurance were adjusted in all models. Finally, likelihood ratio tests were used to evaluate the difference between the two models. All statistical analyses were performed using STATA (v.12.0)

3 Results

The present analysis refers to 7644 participants who were grouped according to their status as non-smokers, initial smokers, former smokers or current smokers. The current smokers were predominantly male, reflecting the large gender gap in smoking rates in China. These 4 groups differed significantly with respect to major socio-demographic characteristics, household debt, medical insurance, BMI, alcohol consumption and symptoms of depression (Table 1).

Table 2 presents the odds ratios for the association between predictors and smoking cessation as well as the likelihood ratio test for the two models. The likelihood ratios for model 1 and model 2 were 0.1143 and 0.1208, respectively. The table also presents the chi-squared value (13.2) for the likelihood ratio test as well as the p-value ($p<0.001$) with one degree of freedom. Thus, adding depression as a predictor variable results in a statistically significant improvement in model fit.

People with depressive symptoms have more than a 1.5-fold risk of abstaining from smoking than those without depression (odds=1.5479, $p<0.001$). Compared with current smokers, certain characteristics, such as middle age (40-59), female, alcohol consumption, BMI$\geq$25 and debt were significantly associated with abstinence from smoking.

Table 3 shows the associations between predictors and depressive symptoms as well as the likelihood ratio test for the other two models. The likelihood ratios of model 3 and model 4 were 0.0387 and 0.0560, respectively, and the chi-squared value (6449.85) for the likelihood ratio test as well as the p-value ($p<0.0001$) with one degree of freedom are listed. The results indicate that adding smoking cessation as a predictor variable significantly increases the fit of the model.

Those who had quit smoking had a more than 1.5-fold risk of having depressive symptoms than current smokers (odds=1.5436, $p<0.001$). In model 4, a relatively high level of education (high than or equal to junior high school), a relatively high BMI ($\geq$25), being in debt, and having health insurance were significantly associated with having depressive symptoms.

Table 1. Prevalence of major characteristics in non-smokers (n=5470), former smokers (n=511), initial smokers (n=341) and current smokers (n=1154)

	Nonsmokers [a]		Former Smokers [b]		Initial smokers [c]		Current smokers [d]		
Characteristic	N	%	N	%	N	%	N	%	***P***
Age									
15-24	657	15	17	3	18	5	16	1	
25-29	262	6	22	4	33	10	32	3	
30-34	320	7	49	10	26	8	81	7	
35-39	395	9	58	11	50	15	150	13	<0.001
40-49	890	20	142	28	90	27	390	34	
50-59	693	15	78	15	46	14	275	24	
>=60	1,284	29	141	28	74	22	201	18	
Gender									
Male	1,367	30	454	90	302	89	1,127	98	<0.001
Female	3,256	70	53	10	37	11	18	2	
Marital status									
Married	3,193	69	416	82	264	78	1,026	90	<0.001
Not married	1,430	31	91	18	75	22	119	10	
Education level									
Illiterate/Primary school	1,158	25	101	20	53	16	149	14	
Junior hign school	1,492	33	201	40	134	40	447	39	<0.001
Senior high school	1,346	29	163	32	105	31	428	37	
>Senior high school	595	13	41	8	47	14	118	10	
Employment									
Employed	3,278	71	360	71	234	69	795	69	0.705
Unemployed	1,345	29	147	29	105	31	350	31	
BMI									
<19	914	20	69	14	41	12	133	12	
19-<25	3,188	69	399	79	256	76	851	74	<0.001
≥25	521	11	39	8	42	12	161	14	
Alcohol consumption									
No	4,524	99	488	97	286	85	876	77	<0.001
Yes	55	1	16	3	49	15	257	23	
Self-rated health									
Good	260	6	24	5	26	8	72	6	
Average	2,308	50	275	54	178	53	602	53	0.1
Bad	2,043	44	207	41	134	40	469	41	
Expenditure on health care									
0	2,050	44	249	49	154	45	535	47	
<100	244	5	26	5	13	4	72	6	0.121
100-600	1,150	25	125	25	88	26	287	25	
>600	1,179	26	107	21	84	25	251	22	
Debt									
No	3,142	68	368	73	232	68	750	66	0.029
Yes	1,473	32	136	27	107	32	394	34	
Dibao									
No	1,587	34	161	32	121	36	360	32	0.179
Yes	3,028	66	346	68	216	64	781	68	
Medical insurance									
Uninsured	3,097	67	274	54	186	55	532	46	<0.001
Insured	1,526	33	233	46	153	45	613	54	
Social Net									
Strong	1,182	26	139	27	98	29	293	26	
Moderate	2,331	50	259	51	161	47	601	52	0.428
Weak	1,110	24	109	22	80	24	251	22	
Important events in family									
Not happened	1,283	28	152	30	95	28	315	28	0.746
Happened	3,340	72	355	70	244	72	830	72	
Depressive symptom									
No	2046	44	195	39	153	45	564	49	0.001
Yes	2596	56	309	61	186	55	580	51	

[a] Non-smokers are respondents who did not smoke cigarettes in 2005 and 2006.
[b] Former smokers are respondents who smoked in 2005 but did not smoked at all in 2006.
[c] Initial smokers are respondents who did not smoke in 2005 but smoked in 2006.
[d] Current smokers are respondents who smoked in 2005 and 2006.

Table 2. Logistic regression predicting smoking cessation status

Characteristic	Smoking cessation status [a]							
	Model 1				Model 2			
	OR	*P*	95% CI [c]		OR	*P*	95% CI [c]	
Age								
15-24	refer				refer			
25-29	0.86	0.748	0.33	2.21	0.84	0.717	0.32	2.18
30-34	0.8	0.622	0.33	1.92	0.74	0.506	0.31	1.79
35-39	0.47	0.079	0.2	1.09	0.45	0.068	0.19	1.06
40-49	0.44	0.053	0.2	1.01	0.42	0.042	0.19	0.97
50-59	0.35	0.015	0.15	0.82	0.34	0.013	0.15	0.79
>=60	0.63	0.287	0.27	1.48	0.62	0.268	0.26	1.45
Gender								
Male	refer				refer			
Female	4.86	<0.001	2.72	8.68	5.02	<0.001	2.8	9
Marital status								
Married	refer				refer			
Not married	1.26	0.215	0.88	1.81	1.23	0.256	0.86	1.78
Education level								
Illiterate/Primary school	refer				refer			
Junior hign school	0.91	0.599	0.64	1.3	0.94	0.758	0.66	1.35
Senior high school	0.77	0.187	0.53	1.13	0.83	0.329	0.56	1.21
>Senior high school	0.71	0.193	0.42	1.19	0.82	0.456	0.49	1.38
Alcohol consumption								
No	refer				refer			
Yes	0.12	<0.001	0.07	0.21	0.12	<0.001	0.07	0.21
BMI								
<19	refer				refer			
19-<25	1.19	0.33	0.84	1.67	1.22	0.264	0.86	1.72
≥25	0.58	0.031	0.35	0.95	0.6	0.043	0.37	0.99
Debt								
No	refer				refer			
Yes	0.69	0.004	0.54	0.89	0.65	0.001	0.51	0.84
Medical insurance								
Uninsured	refer				refer			
Insured	0.84	0.169	0.66	1.08	0.86	0.236	0.67	1.1
Depressive symptom								
No					refer			
Yes					1.55	<0.001	1.22	1.96
R^2	0.1143 [b]				0.1208 [b]			
Likelihood-ratio test	LR chi2(1)=13.2			Prob > chi2=0.0003				

[a] Smoking cessation status included successful quitters (coded as 1) and current smokers (coded as 0).
[b] R^2 of model 1 =0.1143. R^2 of model 2 =0.1208.
[c] CI= confidence interval for OR.

Table 3. logistic regression predicting Depressive symptoms

Characteristic	Depressive Symptom[a]							
	Model 1				Model 2			
	OR	*P*	95% CI[c]		OR	*P*	95% CI[c]	
Age								
15-24	refer				refer			
25-29	1.09	0.535	0.83	1.44	1.35	0.52	0.54	3.35
30-34	1.1	0.511	0.83	1.45	2.13	0.079	0.92	4.94
35-39	1.25	0.094	0.96	1.63	1.6	0.255	0.71	3.59
40-49	1.31	0.024	1.04	1.67	1.74	0.165	0.8	3.82
50-59	1.13	0.341	0.88	1.47	1.55	0.285	0.69	3.46
>=60	1.32	0.03	1.03	1.69	1.44	0.378	0.64	3.24
Gender								
Male	refer				refer			
Female	0.88	0.023	0.79	0.98	0.68	0.153	0.41	1.15
Marital status								
Married	refer				refer			
Not married	1.44	<0.001	1.24	1.68	1.24	0.227	0.88	1.74
Education level								
Illiterate/Primary school	refer				refer			
Junior hign school	0.93	0.363	0.8	1.09	0.7	0.038	0.5	0.98
Senior high school	0.8	0.01	0.68	0.95	0.54	0.001	0.38	0.77
>Senior high school	0.51	<0.001	0.41	0.63	0.26	<0.001	0.16	0.42
Alcohol consumption								
No	refer				refer			
Yes	0.87	0.205	0.7	1.08	0.89	0.394	0.67	1.17
BMI								
<19	refer				refer			
19-<25	0.77	<0.001	0.67	0.89	0.75	0.084	0.54	1.04
≥25	0.64	<0.001	0.52	0.78	0.63	0.032	0.42	0.96
Debt								
No	refer				refer			
Yes	1.92	<0.001	1.72	2.15	1.75	<0.001	1.4	2.2
Medical insurance								
Uninsured	refer				refer			
Insured	0.7	<0.001	0.63	0.79	0.71	0.002	0.57	0.89
Smoke Cessation								
No					refer			
Yes					1.54	<0.001	1.22	1.96
R^2	0.0387[b]				0.0560[b]			
Likelihood-ratio test	LR chi2(1)=6449.85				Prob > chi2=0.0000			

[a] Depressive Symptom included people with depression (coded as 1) and people without depression (coded as 0).
[b] R^2 of model 1 =0.0387. R^2 of model 2 =0.0560.
[c] CI= confidence interval for OR.

4 Discussion

In this study, we addressed several of the gaps in the scientific literature on smoking cessation and depression, specifically in the context of China. We found that among adults in Northwest China who had previously smoked but no longer smoke in 2006 (former smokers) were more likely to be currently depressed than those who smoked in 2005 and 2006 (current smokers). Our results also showed that quitters had a higher prevalence of depressive symptoms, in fact it is not evidence of a clinical diagnosis of depression.

Different from some previous findings that supported a strong association between smoking and mental disorders,[4, 5, 15] we find that smoking cessation was also statistically significantly associated with depression in the context of mainland China. In our study, former smokers demonstrated higher odds of currently suffering from depression than current smokers.

Due to the cross-sectional nature of these data, while we cannot determine the direction of the relationship between the smoking cessation status of former smokers and current depression, we can suggest that there are at least two possible explanations for this association. One, former smokers may become depressed as a result of trying to quit, and two, an identified confounding factor or factors may be associated with both depression and smoking cessation.

The results of a study by Glassman et al. (1990) indicated that when individuals with a history of depression stop smoking, depressive symptoms and, in some cases, serious major depression may ensue.[4, 16] Other studies have also suggested that among smokers with a history of depression, recurrence of depression tends to follow a period of smoking abstinence.[4, 17, 18] The results of these studies support the idea that a history of major depression disorders and smoking cessation affect the risk of a relapse of depression.

Our results also indicate that abstainers were more likely to currently experience depression than were current smokers (table 3). Moreover, we found that successful quitters had the highest rates of depression relative to current smokers, initial smokers and never smokers Table 1. If smoking cessation were to be causally linked to depression, then our findings may be another example of how smoking cessation induces the relapse of depression. In addition, the other conditions significantly associated to smoking cessation other than depressive symptoms, such as age (40-59), female, alcohol consumption, BMI$\geq$25 and debt, *et al*.

Several studies noted the role of monoamine oxidases (MAO) as a pharmacological link between smoking and neurotransmitter processes in the brains of smokers.[19] A study conducted by Fowler (1996) reported that the brains of living smokers show a 40% decrease in the level of monoamine oxidase B relative to non-smokers or former smokers.[19] As MAO B inhibition may result from tobacco smoking, smoking cessation may also affect these pathways, thereby increasing an individual's risk of depression during the period of withdrawal and thereafter.[20] These findings may explain the relationship between smoking abstinence and the re-occurrence of depression.

We were also able to examine associations between smoking cessation and depression that controlled for the existence of economic and behaviour conditions, such as house debt, alcohol consumption and BMI. Many studies exist in the developed countries to prove the impact of economic concerns on smoking cessation.[21–23] A follow-up study from the U.S. indicated that greater financial strain predicted lower abstinence rates among racially/ethnically diverse smokers.[24, 25] In addition, heavy drinking has been associated with a decreased likelihood of smoking cessation,[26] and concern about weight may be a possible predictor of smoking behaviour among youth.[27] In our study, however, we found significant associations between smoking abstinence status and depression even after controlling for the existence of certain economic and behaviour conditions.

However, our finding that people with depression were more likely to be currently abstinent from smoking than those without depression is a novel one Table 2. In our study, the odds ratio for smokers with current depression was higher than those without depression, which is inconsistent with earlier findings,[4] and the likelihood ratio test for two models was statistically significant. We have no clear interpretation for this disparity, which warrants further investigation.

Our study also suffered from several limitations.[28] First, as our data are cross-sectional, great caution must be exercised in deducing causality from them.[29] Second, caution should be used when generalizing our findings to other populations as our study only targeted urban residents in Northwest China. Third, as we mainly examined the economic and behaviour factors of smoking, we did not cover all factors that influence cigarette-smoking status. Fourth, it is not known whether people were already suffered from depression before they quit smoking or if the depressive symptoms took over afterwards.

In conclusion, in the present study, given both the higher prevalence of depression and the higher risk of currently experiencing depression in smoking quitters, government bodies in China should implement appropriate strategies and execute effective measures that involve psychotherapy to reduce the harmful consequences associated with smoking.

References

[1] CDC. (2011). Golbal Adult Tobacco Survey (GATS) (2010) China 2010 Country Report.

[2] Gu D, Kelly TN, Wu X, *et al*. Mortality attributable to smoking in China. *N Engl J Med*, 2009, **360**(2): 150-159. https://doi.org/10.1056/NEJMsa0802902

[3] Prevention, Chinese Center for Disease Control and. (2011). Global Adult Tobacco Survey (GATS) China 2010 Country Report.

[4] Glassman AH, Helzer JE, Covey LS, *et al*. Smoking, smoking cessation, and major depression. *JAMA*, 1990, **264**(12):1546-1549. https://doi.org/10.1001/jama.264.12.1546

[5] Lasser K, Boyd JW, Woolhandler S, *et al*. Smoking and mental illness: A population-based prevalence study. *JAMA*, 2000, **284**(20):2606-2610. https://doi.org/10.1001/jama.284.20.2606

[6] Degenhardt L, Hall W, Lynskey M . Alcohol, cannabis and tobacco use among Australians: a comparison of their associations with other drug use and use disorders, affective and anxiety disorders, and psychosis. *Addiction*, 2001, **96**(11:1603-1614. https://doi.org/10.1080/09652140120080732

[7] Kim O. The relationship of depression to health risk behaviours and health perceptions in Korean college students. *Adolescence*, 2002, **37**(147):575-583.

[8] Haukkala A, Uutela A, Vartiaine E, *et al*. Depression and smoking cessation: the role of motivation and self-efficacy. *Addict Behav*, 2000, **25**(2): 311-316. https://doi.org/10.1016/S0306-4603(98)00125-7

[9] McClave AK, Dube SR, Strine TW, *et al*. Associations between smoking cessation and anxiety and depression among U.S. adults. *Addictive behaviours*, 2009, **34**(67):491-497. https://doi.org/10.1016/j.addbeh.2009.01.005

[10] Lam TH, Stewart SM, Ho SY, Lai, *et al*. Depressive symptoms and smoking among Hong Kong Chinese adolescents. *Addiction*, 2005, **100**(7): 1003-1011. https://doi.org/10.1111/j.1360-0443.2005.01092.x

[11] Hitsman B, Borrelli B, McChargue DE, *et al*. History of depression and smoking cessation outcome: A meta-analysis. *Journal of Consulting and Clinical Psychology*, 2003, **71**(4):657-663. https://doi.org/10.1037/0022-006X.71.4.657

[12] Johnson EO, Breslau N. Is the association of smoking and depression a recent phenomenon? *Nicotine Tobacco Research*, 2006, **8**(2):257-262. https://doi.org/10.1080/14622200600576644

[13] Ma X, Xiang YT, Cai ZJ,*et al*. Smoking and psychiatric disorders in the rural and urban regions of Beijing, China: a community-based survey. *Drug Alcohol Depend*, 2009, **100**(1-2):146-152. https://doi.org/10.1016/j.drugalcdep.2008.10.002

[14] Radloff LS. The CES-D Scale: A Self-Report Depression Scale for Research in the General Population. *Applied Psychological Measurement*, 1977, **1**(3):385-401.

[15] Cuijpers P, Smit F, ten Have M, *et al*. Smoking is associated with first-ever incidence of mental disorders: a prospective population-based study. *Addiction*, 2007, **102**(8):1303-1309. https://doi.org/10.1111/j.1360-0443.2007.01885.x

[16] Niaura R, Abrams DB. Stopping smoking: a hazard for people with a history of major depression? *Lancet*, 2001, **357**(9272):1900-1901. https://doi.org/10.1016/S0140-6736(00)05089-3

[17] Covey LS, Glassman AH, Stetner F. DEPRESSION AND DEPRESSIVE SYMPTOMS IN SMOKING CESSATION. *Comprehensive Psychiatry*, 1990, **31**(4): 350-354. https://doi.org/10.1016/0010-440X(90)90042-Q

[18] Tsoh JY, Humfleet GL, Munoz RF, *et al*. Development of major depression after treatment for smoking cessation. *American Journal of Psychiatry*, 2000, **157**(3):368-374. https://doi.org/10.1176/appi.ajp.157.3.368

[19] Fowler JS, Logan J, Wang, GJ, *et al*. Monoamine Oxidase and Cigarette Smoking. *NeuroToxicology*, 2003, **24**(1):75-82. https://doi.org/10.1016/S0161-813X(02)00109-2

[20] Berlin I, M Anthenelli R. Monoamine oxidases and tobacco smoking. *The International Journal of Neuropsychopharmacology*, 2001, **4**(01):33-42. https://doi.org/10.1017/S1461145701002188

[21] Siahpush M, Carlin JB. Financial stress, smoking cessation and relapse: results from a prospective study of an Australian national sample. *Addiction*, 2006, **101**(1): 121-127. https://doi.org/10.1111/j.1360-0443.2005.01292.x

[22] Siahpush M, Spittal M, Singh GK. Smoking cessation and financial stress. *Journal of Public Health*, 2007, **29**(4):338-342. https://doi.org/10.1093/pubmed/fdm070

[23] Volpp KG, Troxel AB, Pauly MV, *et al*. A Randomized, Controlled Trial of Financial Incentives for Smoking Cessation. *New England Journal of Medicine*, 2009, **360**(7):699-709. https://doi.org/10.1056/NEJMsa0806819

[24] Gong Y, Zhang X, Zou H, *et al*. Debt and depression among the Dibao population in Northwest China. *International Journal of Social Psychiatry*, 2013, **60**(7):637-645. https://doi.org/10.1177/0020764013511068

[25] Kendzor DE, Businelle MS, Costello TJ, *et al*. Financial Strain and Smoking Cessation Among Racially/Ethnically Diverse Smokers. *American Journal of Public Health*, 2010, **100**(4):702-706. https://doi.org/10.2105/AJPH.2009.172676

[26] Dollar KM, Homish GG, Kozlowski LT, *et al*. Spousal and Alcohol-Related Predictors of Smoking Cessation: A Longitudinal Study in a Community Sample of Married Couples. *American Journal of Public Health*, 2009, **99**(2): 231-233. https://doi.org/10.2105/AJPH.2008.140459

[27] Leatherdale ST, Wong SL, Manske SR, *et al*. Susceptibility to smoking and its association with physical activity, BMI, and weight concerns among youth. *Nicotine Tobacco Research*, 2008, **10**(3):499-505. https://doi.org/10.1080/14622200801902201

[28] Luo J, Qu Z, Rockett I, *et al*. Employment status and self-rated health in north-western China. *Public Health*, 2010, **124**(3):174-179. https://doi.org/10.1016/j.puhe.2010.02.001

[29] Diomidus M. Epedemiological study designs. *Studies in Health Technology and Informatics*, 2002, **65**:9.

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RESEARCH ARTICLE

Detecting Dengue Fever in Children: Using Sequencing Symptom Patterns for An Online Assessment Approach

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Abstract: Background: Dengue fever (DF) is an important health problem in Asia. We examined it using its clinical symptoms to predict DF. Methods: We extracted statistically significant features from 17 DF-related clinical symptoms in 177 pediatric patients (69 diagnosed with DF) using the unweighted summation score and the non-parametric H^T person fit statistic, which jointly combine the weighted score (yielded by logistic regression) to predict DF risk. Results: Six symptoms (Family History, Fever $\geq$ 39°C, Skin Rash, Petechiae, Abdominal Pain, and Weakness) significantly predicted DF. When a cutoff point of 1.03 (p = 0.26) suggested combining the weighted score and the H^T coefficient, the sensitivity was 0.91 and the specificity was 0.76. The area under the ROC curve was 0.88, which was a better predictor: specificity was 5.56% higher than for the traditional logistic regression. Conclusions: Six simple symptoms analyzed using logistic regression were useful and valid for early detection of DF risk in children. A better predictive specificity increased after combining the non-parametric H^T coefficient to the weighted regression score. A self-assessment using patient smart phones is available to discriminate DF and may eliminate the need for a costly and time-consuming dengue laboratory test.

Keywords: dengue fever, H^T person mapping statistic, logistic regression, score summation, receiver operating characteristic curve

1 Introduction

Dengue fever (DF) is one of the most common arthropod-borne viral diseases worldwide,[1] especially in South East Asia, Africa, the Western Pacific, and the Americas.[2,3]

There is, however, no accurate and speedy diagnostic screening test for DF at an early stage because its signs and symptomse.g., fever, headache, and myalgiaare similar to those of other illnesses.[4–6] Some studies[4,5] that used a univariate analysis report that the presumptive diagnosis of DF is imprecise. Multivariate logistic regressions also do not significantly distinguish patients with dengue from those with other febrile illnesses.[7] The multivariate discrimination analyses reported a sensitivity and a specificity 0.76, and an area under the receiver operating characteristic (ROC) curve (AUC) of 0.93, but costly laboratory tests (Dengue Duo IgM & Rapid Strips; Panbio, Queensland, Australia)[8–11] were needed before DF was serologically confirmed.

DF symptoms are usually assessed using a dichotomous (i.e., absent versus present) evaluation. The dependent variable (DF^+ versus DF^-) predicted using independent evaluations with a weighted summation score is more accurate than that using simple evaluations with an unweighted summation score. So far, there has been no published study that has reported using the specific sequence of symptoms reported or observed in specific patients suspected of having DF. All published studies to date still report using only a standard group of symptoms with an unweighted summation score that apply to a general group of patients that might have DF.

The non-parametric HT fit statistic has been used in education and psychometrics to identify aberrant test respondents.[12,13] It is a transposed formulation of a scalability coefficient for items (e.g., symptoms in this study) and evidently the best among 36 person fit statistics for detecting abnormal behaviors.[14]

In the present study, we used the H^T coefficient com-

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bined with weighted and unweighted variables to examine whether these combinations provide a valid and reliable approach for the early detection of DF in children.

2 Materials and methods

2.1 Sample and clinical symptoms

The sample of 177 pediatric patients ($\leq$ 16 years old; DF$^+$:69; DF$^-$:108) was the same as in our previous paper.[8] Guided by the literature,[5–7] we collected nineteen DF-related clinical symptoms from the patients medical records to develop the initial set of itemsdesignated as 0=absent or 1=present to screen for DF infection: (i) personal history of DF, (ii) family history of DF, (iii) mosquito bites within the previous 2 weeks, (iv) fever $\geq$ 39°C, (v) biphasic fever, (vi) rash, (vii) petechiae, (viii) retro-orbital pain, (ix) bone pain (arthralgia), (x) headache, (xi) myalgia, (xii) abdominal pain, (xiii) anorexia, (xiv) occult hematuria, (xv) stool occult blood, (xvi) cough, (xvii) sore throat, (xviii) soft (watery) stool, and (xix) flushed skin. Data from these patients charts were obtained and approved by the Research Ethics Review Board of the Chi-Mei Medical Center.

2.2 The H^T fit statistic

H^T is defined for the persons of a dichotomous dataset with L items (in columns) and N persons (in rows),[12] where X_{ni} is the scored (0,1) response of person n to item i, and $P_n = S_n/L$. Here, S_m is the raw score for person m, and S_n is the raw score for person n.

$$\mathrm{H}^T(n) = \frac{\sum\limits_{m=1,m\neq n}^{N}\left(\left[\sum\limits_{i=1}^{L} X_{ni}X_{mi}\right]/L - P_nP_m\right)}{\sum\limits_{m=1,m\neq n}^{N}(min[P_n(1-P_m).P_m(1-P_n)])} \quad (1)$$

H^T is the sum of the covariances between person n and the other persons divided by the maximum possible sum of those covariances, so that the range of H^T is -1 to +1. When the responses by person n are positively correlated with those of all the other persons, then $H^T(n)$ will be positive. In contrast, when the responses by person n are negatively correlated with those of all the other persons, then $H^T(n)$ will be negative. When person's responses are random, $H^T(n)$ will be close to zero[11]. We hypothesized that DF$^+$ patients have different H^T coefficients than do DF$^-$ patients. All DF$^+$ group members were sequenced to the DF$^-$ group members to obtain an H^T coefficient using equation (1).

2.3 Selecting symptoms and determining predictor variables

All symptoms were examined by the probability of Type I error using the following three steps in Figure 1 to determine predictor variables. First, each symptom was separately examined by the univariate approach using a χ^2 test and logistic regression, respectively, for identifying a significant association with DF. Second, two models (i.e., the univariate and the multivariate approaches) were investigated for determining valid predictor variables associated with DF when the probability of Type I error is less than 0.05. Third, the predictor variables were used in a weighted combination for discriminating patients suspected with dengue virus infection.

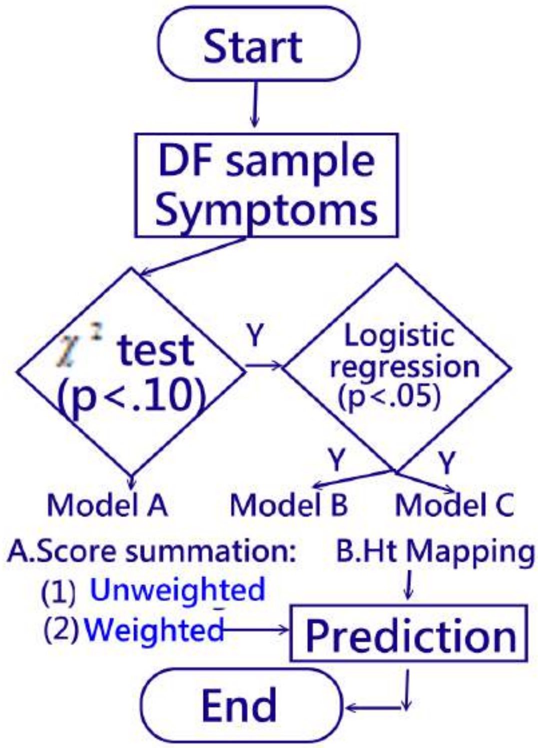

Figure 1. Overall study concept and the flow chart

2.4 Detecting dengue fever: a comparison of three models

The efficacy of three models (A, B, and C) for detecting dengue fever was examined: (i) A comparison was made using univariate logistic regression in Model A to examine effects through the AUC yielded by Unweighted (i.e., summed item) scores, Weighted (i.e., logistic regression) scores, and H^T coefficients, respectively, (ii) Multivariate logistic regression with the three aforementioned factors combined was used in Model B,

(iii) after selecting the significant variables in Model B, the combined predictive variables were analyzed using multivariate logistic regression in Model C to obtain effective weighted coefficients, and (iv) finally, we wanted to use a single continuous variable yielded by the combined predictive variables in Model C to compare the AUC with the counterparts in Model A and C.

2.5 Statistical tools and data analyses

SPSS 15.0 for Windows (SPSS Inc., Chicago, IL) and MedCalc 9.5.0.0 for Windows (MedCalc Software, Mariakerke, Belgium) were used to calculate (i) the probability of false positives (Type I error) using a χ^2 test and logistic regression, (ii) Youden J index (the higher, the better), AUC (area under the ROC curve), sensitivity, specificity, and the cutoff point at maximal summations of specificity and sensitivity, (iii) correlation coefficients among variables of unweighted, weighted, and H^T scores.

3 Results

Sixty-nine pediatric patients clinically diagnosed with DF and 108 with no evidence of DF infection were included in this study (Table 1). A χ^2 test and logistic regression analyses showed that only six symptoms (Family History, Fever $\geq$ 39°C, Skin Rash, Petechiae, Abdominal Pain, and Weakness) were significant for assessing the likelihood of DF (Table 2).

Table 1. Demographic characteristics of the study sample

Demographical Variables		DF(-)[1] n	DF(-)[1] %	DF(+)[2] n	DF(+)[2] %	Total n	Total %	P-value[3]
Gender	Female	47	44	29	42	76	43	0.845
	Male	61	57	40	58	101	57	
Age(years)	0-4	48	44	11	16	59	34	0.005
	5-9	24	22	20	29	44	25	
	9-16	36	33	37	54	73	42	

[1]DF(+): patients with a positive dengue fever strip test
[2]DF(-): patients with a negative dengue fever strip test
[3]P-values were determined by the test

Table 2. Logistic analysis of symptoms for the patients suspected with dengue virus infection using the univariate approach

Symptom		DF(-)		DF(+)		Total		Chi-square test		Logistic	
Variable	Present	n	%	n	%	n	%	X^2	P-value	B	P-value
Family history	No	79	73	40	58	119	67	3.74	0.053	1.35	0.002
	Yes	29	27	29	42	58	33				
High fever of 39°C	No	87	81	37	54	124	70	13.30	<.001	1.48	0.048
	Yes	21	19	32	46	53	30				
Skin rash	No	82	76	20	29	102	58	36.09	<.001	2.63	0.000
	Yes	26	24	49	71	75	42				
Petechiae	No	106	98	60	87	166	94	7.29	0.007	2.34	0.026
	Yes	2	1.9	9	13	11	6.2				
Abdominal pain	No	104	96	53	77	157	89	14.03	<.001	2.89	0.000
	Yes	4	3.7	16	23	20	11				
Weak sense	No	90	83	48	70	138	78	3.88	0.049	0.98	0.048
	Yes	18	17	21	30	39	22				
Constant										-3.3	

P-values were determined by the test and the Wald test of Logistic regression

Comparisons of the AUCs for the three study models (A, B, and C) showed that the weighted variable (derived by the Logistic regression) and the HT coefficient can be jointly used for predicting DF risk using equation (2):

$$Logit = -3.32 + 0.93 \times weighted\_score + 1.92 \times H^T\_coefficient \quad (2)$$

The risk probability can be computed using the transformed equation (3):

$$p = \frac{exp\,(logit)}{1 + exp\,(logit)} \quad (3)$$

where *logit* denotes a unit of log odds.

A cutoff point of 1.03 (P = 0.26) was determined using the combined predictive variables in Model C: sensitivity = 0.91, specificity = 0.76, and AUC = 0.88 (Figure 2 and Table 3). Predictive power was better: specificity was 5.56% (i.e., 75.93-70.37 shown in Table 3) higher than when using traditional logistic regression; however, the AUC was slightly lower (0.72) than when using the unweighted (0.84) and the weighted (0.87) variables (Table 2). The HT coefficients related to the weighted and unweighted scores were 0.26 and 0.22, respectively. The weighted score has a higher correlation coefficient than does the unweighted score to the H^T coefficients.

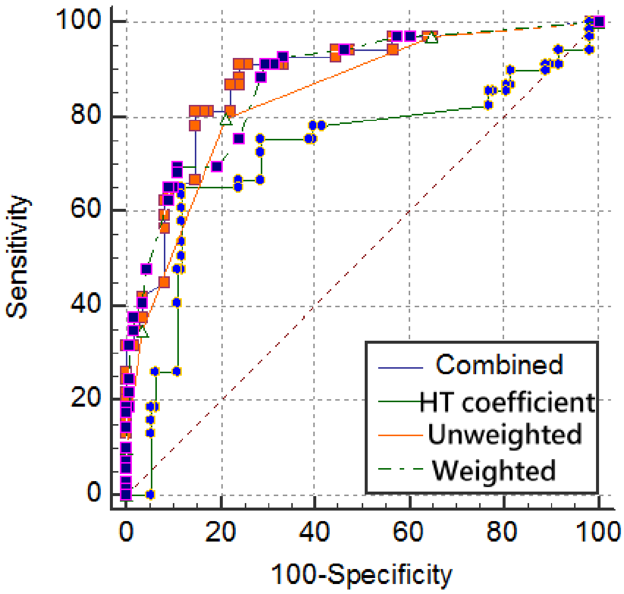

Figure 2. Four models plotted by ROC curves

A snapshot on a smart phone responding to questions (Figure 3, top) was generated and the results for assessing whether the patient has DF (Figure 3, bottom) were determined, which indicated that patients suspected of having DF can directly scan the QR-code to obtain

Table 3. Comparisons of AUC for the study models

Approach	Logistic		ROC curve analysis				
Steps	B[a]	P-value	AUC	Youden J[b]	Cut point	Sensitivity	Specificity
(1) Model A:Univariate approach with a single variable comparing to the DF using Logistic regression and ROC analysis							
Unweight[c]	1.60*	<0.001	0.84	0.58	>1.00	79.7	78.7
Weight[d]	0.97*	<0.001	0.87	0.61	>-0.93	91.3	69.4
H[t] coeff.[e]	3.75*	<0.001	0.72	0.53	>0.15	65.2	88.0
(2) Model B: Multivariate approach with combined these three variables in regressing the DF using Logistic regression							
Unweight	0.31	0.595					
Weight	0.77*	0.014					
H[t] coeff.	3.08*	0.001					
Constant	-1.03	0.350					
(3) Model C: Combined these two significant predictor variables using Logistic regression							
Weight	0.919*	<0.001					
H[t] coeff.	2.962*	0.001					
Constant	-0.463	0.75					
(4) A single continuous variable yielded by the combined predictor variables							
Combined[f]	1	<0.001	0.89	0.67	>-0.65	87	79.6

[a]: coefficient of Logistic regression
[b]: Youden J index
[c]: item-score summation method
[d]: multiplying item-score with the weighted regression coefficient
[e]: the Ht coefficient
[f]: using the two combined variables to predict patients DF
*:p<0.05

their DF *logit* scores (or the risk probability) and examine whether these 6 symptoms are useful for predicting a high DF risk (>1.03 *logits* or $P \geqslant 0.26 = exp(-1.03\,logits)/(1+exp(-1.03\,logits))$.

4 Discussion

We found that using the H^T coefficient yielded predictions that were 5.56% more specific (i.e., 75.93-70.37 shown in Table 3) than those of traditional logistic regression. The H^T index is promising when the patient sequence symptom pattern is compared with the DF$^+$ group to detect dengue fever in children. It can be combined with the weighted summation score to jointly predict the DF risk and then to report that risk on smartphones.

The H^T coefficient has been used in education and psychometrics to identify aberrant test respondents.[12, 13] Although some have used item response theory (IRT) fit statistics (e.g., outfit mean square error > 2.0) to select abnormal responses that indicate cheating, careless responding, lucky guessing, creative responding, or random responding,[15] our literature review revealed no published papers that reported using the H^T coefficient in medical settings, especially for detecting individual aberrant response patterns different from the study reference sample, or, like the current study, identifying the DF risk by comparing their sequence symptom pattern to that of the DF$^+$ group.

A diagnosis of DF is usually confirmed by three steps: (i) observing DF-related symptoms, (ii) testing laboratory data such as white blood cells (WBCs) and platelets (PLTs), and (iii) serologically verifying DF using dengue IgM and IgG antibodies, polymerase chain reaction (PCR) analysis, and virus isolation tests. The latter two are relatively expensive. It is needed to develop a self-assessment approach (e.g., scanning QR-code, responding questions, and obtaining the DF risk on his/her smart phone) (1) helping patients for consultation at an earlier stage, (2) prompting doctors sampling patient laboratory data when he/her DF risk reaches a cutpoint of *P*=0.26=exp(-1.03 *logits*)/(1+exp(-1.03 *logits*)).

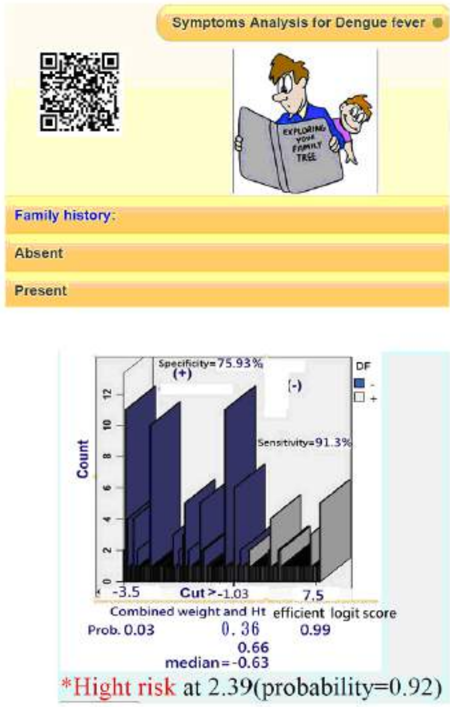

Figure 3. Figure 3 Snapshots on a smart phone responding questions (top) and the result (bottom) for assessing the patient DF

We found that the weighted score was a better predictor than was the unweighted score (see Model A and Model B in Table 3). However, we still see so many scales in medical setting using unweighted summation scores to determine the presence or absence of disease. Along with the smartphones popularly used in the technical age, the way of obtaining the DF risk on smartphones using the combined H^T coefficient and weighted scores is available and worth recommending to healthcare providers to use for detecting the risk for DF.

This study has some limitations. First, the DF cutpoint based on the symptoms of our study sample might be biased toward that population. Moreover, we did not remove abnormal data when the H^T coefficient was less than the critical value of 0.22, which best identifies aberrantly responding examinees.[14] Second, although the sample size was small, using the Rasch H^T coefficient combined with the AUC yielded highly accurate discriminatory screening. This finding, however, requires confirmation in prospective studies of other regions with a substantial incidence of DF.

5 Conclusions

Analyzing six simple symptoms using logistic regression is useful and valid for the early detection of DF risk in children. Combining the Rasch H^T coefficient with the weighted score yields a prediction that is 5.56% more specific than does traditional logistic regression. A self-assessment app using patient smartphones is available to help people suspected of having DF, and it might eliminate the need for costly and time-consuming laboratory tests.

6 Competing interests

The authors declare that they have no competing interests.

7 Authors contributions

T.-W.C. and S-C.K. conceived and designed the study, performed the statistical analyses and were in charge of recruiting study participants. W.-S.L. and T.-W.C. helped design the study, collected information and interpreted data. All authors read and approved the final article. This research was supported by grant Chi-Mei Foundation Hospital research CMFCR10593 from the Chi-Mei Medical Center. The authors have no other funding or conflicts of interest to disclose.

References

[1] World Health Organization. Dengue and Dengue Haemorrhagic Fever. Fact sheet No. 117. Geneva: World Health Organization, 2002.

[2] Henchal EA, Putnak JB. The dengue viruses. Clin Microbiol Rev, 1990, **3**(4):376-396. https://doi.org/10.1128/CMR.3.4.376

[3] Gubler DJ. Dengue and dengue hemorrhagic fever. Clin Microbiol Rev, 1998, **11**(3):480-496. https://doi.org/10.1016/S1045-1870(97)80003-9

[4] Phuong HL, de Vries PJ, Nga TT, et al. Dengue as a cause of acute undifferentiated fever in Vietnam. BMC Infect Dis, 2006, **6**:123. https://doi.org/10.1186/1471-2334-6-123

[5] Nunes-Arajo FR, Ferreira MS, Nishioka SD. Dengue fever in Brazilian adults and children: assessment of clinical findings and their validity for diagnosis. Ann Trop Med Parasitol, 2003, **97**(4):415-419. https://doi.org/10.1179/000349803235002263

[6] Hammond SN, Balmaseda A, Prez L, et al. Differences in dengue severity in infants, children, and adults in a 3-year hospital-based study in Nicaragua. Am J Trop Med Hyg, 2005, **73**(6):1063-1070. https://doi.org/10.4269/ajtmh.2005.73.1063

[7] Potts JA, Rothman AI. Clinical and laboratory features that distinguish dengue from other febrile illnesses in endemic populations. Trop Med Int Health, 2008, **13**(11):1328-1340. https://doi.org/10.1111/j.1365-3156.2008.02151.x

[8] Lai WP, Chien TW, Lin HJ, Su SB, Chang CH. A screening tool for dengue fever in children. Pediatr Infect Dis J, 2013, **32**(4):320-324. https://doi.org/10.1097/INF.0b013e31827e111e

[9] Lai WP, Chien TW, Lin HJ, Kan WC, Su SB, Chou MT. An approach for early and appropriate prediction of dengue fever using white blood cells and platelets. HealthMed, 2012, **6**(7):806-812.

[10] Kittigul L, Suankeow K. Use of a rapid immunochromatographic test for early diagnosis of dengue virus infection. Eur J Clin Microbiol Infect Dis, 2002, **21**(3):224-226. https://doi.org/10.1007/s10096-001-0691-z

[11] Vaughn DW, Nisalak A, Kalayanarooj S, et al. Evaluation of a rapid immunochromatographic test for diagnosis of dengue virus infection. J Clin Microbiol, 1998, **36**(1):234-238.

[12] Sijtsma K. A coefficient of deviant response patterns. Kwantitatieve Methoden, 1986, **7**(22):131-145.

[13] Linacre JM. A comment on the HT person fit statistic. Rasch Meas Trans, 2012, **26**(1):1358.

[14] Karabatsos G. Comparing the aberrant response detection performance of thirty-six person-fit statistics. Appl Meas Educ, 2003, **16**(4):277-298. https://doi.org/10.1207/S15324818AME1604_2

[15] Linacre JM. Optimizing rating scale category effectiveness. J Appl Meas, 2002, **3**(1):85-106.

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RESEARCH ARTICLE

A dashboard on Google Maps to show the most influential author on the topic of health behavior: A Bibliometric Analysis

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Abstract: Background:Health behavior is an action taken by a person to maintain, attain, or regain good health and to prevent illness. As such, health behavior reflects a person's health beliefs and attracts many published papers in academics. However, who is the most influential author (MIA) remains unknown. Objective: The purpose of this study is to apply the algorithm of between centrality(BC) in social network analysis (SNA) to select the MIA on the topic of health behavior using the visual displays on Google Maps. Methods: We obtained 3,593 abstracts from Medline based on the keywords of (health [Title]) and (behavior [Title] or behaviour [Title]) on June 30, 2018. The author names, countries/areas, and author-defined keywords were recorded. The BCs were applied to (1) select the MIA using SNA; (2) display the countries/areas distributed for the 1st author in geography, (3) discover the author clusters dispersed on Google Maps, and (4) investigate the keywords dispersed for the cluster related to the MIA on a dashboard. Pajek software was performed to yield the BC for each entity (or say node). Results: We found that the MIA is Spring, Bonnie (US). All visual representations that are the form of a dashboard can be easily displayed on Google Maps. The most influential country and the keywords are the US and health behavior. Readers are suggested to manipulate them on their own on Google Maps. Conclusion: Social network analysis provides wide and deep insight into the relationships with the pattern of international author collaborations. If incorporated with Google Maps, the dashboard can release much more information regarding our interesting topics for us in academics. The research approach using the BC to identify the same author names can be applied to other bibliometric analyses in the future.

Keywords: Gini coefficient, authorship collaboration, Google Maps, social network analysis, health behavior

1 Introduction

Health behavior is an action taken by a person to maintain, attain, or regain good health and to prevent illness.[1] Health behavior reflects a person's health beliefs. Some common health behaviors are exercising regularly, such as eating a balanced diet, and obtaining necessary inoculations. Even if the signs of Attention deficit hyperactivity disorder (ADHD) are included in the research of health behavior.[2]

As of June 30, 2018, there are 3,593 abstracts in search from Medline based on the keywords of (health[Title]) and (behavior[Title] or behaviour [Title]). Who are the most influential author(MIA) or the most productive author(MPA) remains unknown.

It is hard to find the relationship using the traditional research approach. For instance, we often can only get a sense of our concerned entities independent of each other. This is, when many customers purchase their goods by placing them in a shopping cart, the traditional way to calculate the quantity of each goods instead of analyzing their correlations. An apocryphal story was often told to tell us the concept of co-occurrence that is about beer and diaper sales which usually goes along with a strong correlation on Friday.[3–5] Many data scientists have developed ways to discover new knowledge from the vast quantities of increasingly available information,[6] particularly applying social network analysis (SNA)[7–10] to big data analysis.

Authorship collaboration using SNA is an example illustrated by many authors in recent years[7] because coauthors among researchers form a type of social network.

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Many of those authors[7–10] applied degree centrality to analyze or select their authors of interest. None to date used betweenness centrality(BC) to study their entities. Particularly, the duplicate names in their bibliometric study data might result in biases because some different authors with the same name exist.[10] We thus are interested in using BC to select the MIA on the topic of health behavior and investigating other interesting features such as author countries/areas and the keyword dispersions in clusters.

Google maps have provided users to gain an overall geospatial visualization.[11,12] However, few applied Google Maps to display author collaboration with a dashboard format. Our aims applied the BC algorithm[13,14] to select the MIA and display the pattern of international author collaboration in health behavior by (1)selecting the MIA using SNA; (2)displaying the countries/areas distributed for the 1st author in geography, (3)discovering the author clusters dispersed on Google Maps, and (4) investigating the keywords dispersed for the cluster related to the MIA on a dashboard.

2 Methods

2.1 Data Collection

By searching the PubMed database (Pubmed.org) maintained by the US National Library of Medicine, we used the keywords of (health[Title]) and (behavior[Title] or behaviour [Title]) on June 30, 2018, and downloaded 3,593 articles. The inclusion criteria are all downloaded abstracts based on the type of Journal Article. Ethical approval was not necessary for this study because all the data were obtained from the Medline library on the Internet.

2.2 Social network analysis and Pajek software

Social network analysis (SNA)[15] was applied to explore the pattern of entities in a system using the software of Pajek.[16] In keeping with the Pajek guidelines, we defined an author (or paper keyword) as a node that is connected to other nodes through the edge (or say the relation). Usually, the weight between two nodes is defined by the number of connections.

Centrality is a vital index to analyze the network. Any individual or keyword lies in the center of the social network will determine its influence on the network and its speed to gain information.[13,14,17] The Betweenness centrality(BC) is used in this study.

2.3 The pattern of author collaboration on health behavior

The countries/areas of the 1st author for each published paper were extracted for showing the distribution of countries/areas on Google Maps.

The bigger bubble means the most pivotal role played as a bridge in the network if the BC algorithm is performed. The wider line indicates, the stronger relations between the two (i.e., the nation or the author). Clusters separated by the algorithm of the partition communities are filled with bubbles in different colors.

Similarly, the authors and keywords of medical subject headings(MESH) with the most influential power were extracted by the SNA method and shown on Google Maps. All of which were selected by the top 100 authors first and screened out the largest cluster as the base to define the popular MESH terms, see Figure 1.

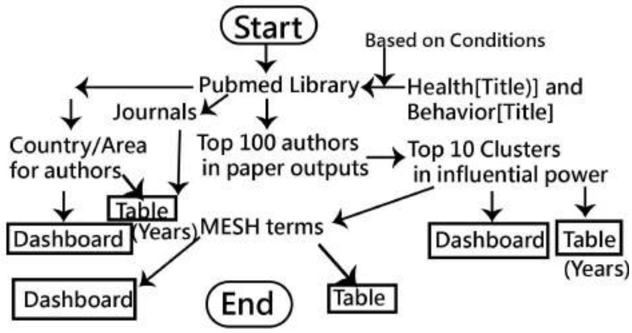

Figure 1. Study flowchart

3 Results

3.1 The most influential author

The most productive author with ten article regarding health behavior is Loprinzi, Paul D from the US, see Table 1. The MIA with some 141 members in the cluster is the author Spring, Bonnie from the US, see the top of Table 2 when the correlations among coauthors were considered in this cluster analysis.

In Table 2 we show many cluster density coefficients. The CC means the cluster coefficient constructed by the number of triangle relations divided by the possible triangle relations in the cluster. The t-statistics is the t-value for the CC. The density indicates the number of connection lines divided by the possible number(= $n \times (n-1)/2$, where n=the number of members in the cluster). The Weighted coefficient allows the duplicate connection lines related to the possible number of connection. The EI is derived from the formula=(external relations minus the internal relation) divided by the sum of external and internal relations). The node=n, The Degree denotes the total unique number of connection. The Dweighted allows the duplicate number of connections in the cluster.

The dispersion of coauthor clusters is shown in Figure 2. The biggest one is related to the MIA Spring, Bonnie(US). Interested readers are recommended linking to the reference.[18]

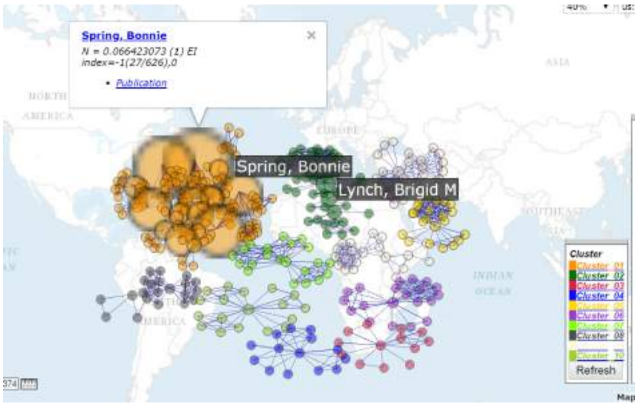

Figure 2. Dispersion of coauthor clusters

3.2 Journals and the trend on health behavior

A total of 3,591 eligible abstracts were included in the current study of health behavior for journal analysis. The most numbers of journals in production outputs are ed(69 papers) followed by Health Psychol(55) and Prev Med(54), see Table 3. All of those Top ten are included by the journal citation reports with impact factors.

3.3 Author countries/areas and their relations using the betweenness centrality

A total of 2,711 eligible papers with complete author countries/areas based on journal article are shown in Table 4. We can see that the most number of papers are from the US(1438,53%) followed by Canada(93, 3.4%), Netherlands(82, 3%), the UK(75, 2.8%) and China(75, 2.8%). The trend in the number of publications is present in the column of growth in Table 4 (in the most left column). All continents present a positive increase in paper publications.

The diagram is shown by SNA using the algorithm on Google Maps in Figure 3 and displays the pattern of author's collaboration among countries/areas based on the topic of health behavior. As expected, the US plays an influential role with the biggest bubble in Figure 3.Interested authors are recommended to click the bubble of interest to see details on a website at the reference.[19]

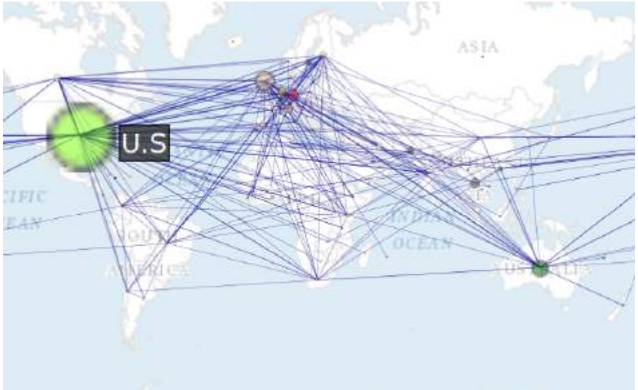

Figure 3. Dispersion of author countries/areas

3.4 Keywords on health behavior

The most influential keyword is health behavior, see Figure 4. Interested authors are suggested click the bubble of interest to see details on Google Maps at the reference.[20] The most number of nodes in the cluster are health behavior (33), psychology(24), and diagnosis(21), See the bottom in Table 2. When comparing the coefficients of CC and EI between clusters of authors and MESH terms in Table 2, we can see that the author clusters earn the higher density of CC, but the MESH terms gain the greater EI which means that MESH terms have somewhat relations among clusters. In contrast, the author clusters show independent among clusters(i.e., EI=external linkages minus internal connection divided by the sum of both external and internal number of connections).

Figure 4. Dispersion of MESH terms

4 Discussion

This study found that the MIA is Spring, Bonnie(US). All visual representations that are the form of a dash-

Table 1. The most productive authors

Author	Country	Year											Total
		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	
Loprinzi, Paul D	US						2	3	2	3			10
Hedman, Erik	Sweden						3	2	2		2		9
Peltzer, Karl	South Africa		2						1	3	2		8
Jung, Minsoo	South Korea					2	2	3			1		8
Han, Kyungdo	South Korea								1	1	2	2	6
Hagger, Martin S	Australia								1	2	2	1	6
Jimenez, Daniel E	US								2	2	2		6
Rogers, Laura Q	Canada		2				2			2			6
Epton, Tracy	UK	2					2		2				6
Lovallo, William R	US					2	2	2					6

Table 2. The density coefficients for the most influential author clusters

No	CC	t	Density	Weighted	EI	Node	Degree	DWeighted	Name
A. Author cluster									
1	0.67	10.64	0.06	0.08	-1	141	625	752	Spring, Bonnie(US)
2	0.62	5.59	0.16	0.18	-1	52	217	243	Lynch, Brigid M(Australia)
3	0.66	4.21	0.36	0.39	-1	25	107	116	Sun, Xinying(China)
4	0.92	10.5	0.54	0.58	-1	22	125	135	Simons-Morton, Bruce(US)
5	0.68	4.04	0.42	0.51	-1	21	89	107	Malta, Deborah Carvalho(Brazil)
6	0.72	4.52	0.36	0.39	-1	21	75	82	Krist, Alex H(US)
7	0.73	4.53	0.42	0.47	-1	20	79	90	Baranowski, Tom(US)
8	0.82	6.08	0.39	0.39	-1	20	74	74	Beehler, Gregory P(US)
9	0.5	2.31	0.27	0.33	-1	18	42	50	Hagger, Martin S(Australia)
10	0.49	1.95	0.37	0.41	-1	14	34	37	Sharma, Manoj(US)
B. MESH term cluster									
1	0.35	2.08	0.26	0.59	-0.08	33	135	311	health behavior
2	0.55	3.09	0.25	0.36	-0.06	24	70	99	psychology
3	0.67	3.93	0.33	0.47	-0.14	21	69	99	diagnosis
4	0.45	2.14	0.26	0.54	-0.02	20	49	102	standards
5	0.37	1.59	0.29	0.62	0.15	18	44	95	health promotion
6	0.56	2.14	0.52	1.14	-0.11	12	34	75	pharmacology
7	0.4	1.31	0.38	1.36	0.32	11	21	75	organization & administration
8	0.67	2.39	0.44	0.61	0	9	16	22	adverse effects

Table 3. Paper productions for top 10 journals

Journal Name	Year											Total	IF
	1951--2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018		
Soc Sci Med	43	2	1	1	4	6	2	3	2	3	2	69	2.797
Health Psychol	31		1	1		4	5	4	5	2	2	55	3.458
Prev Med	30	2	5	1	2		4	3	4	3		54	3.434
PLoS One	0		4	1	3	7	6	5	8	7	6	47	2.806
Am J Health Behav	19	4	5	1	2	2	4	2	1	3		43	1.479
BMC Public Health	1	1	2	6	4	6	4	5	5	3	4	41	2.265
J Med Internet Res	2	1	1	1	3	5	4	4	10	7	2	40	5.175
J Sch Health	28		3	2	1			1	1		1	37	1.434
Patient Educ Couns	9	3	1	4	4	2	5	2	7			37	2.429
Health Educ Res	27	2		1		1			1	1		33	1.816
Others	2929	232	259	281	328	358	399	439	463	409	3307		
Total	1606	113	157	144	179	205	220	242	270	266	189		

Table 4. Dispersion of the 1st authors countries/areas over the years

Continent	<-2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total	%	Growth
AFRICA	11	2	6	2	4	8	3	5	7	10	7	65	2.4	0.7
Ethiopia	0		2		2	3	1	1	4	3	1	17	0.6	0.6
Nigeria	5		2	1	1		1	1	1	2		14	0.5	0.3
Kenya	1					1	1	1		2	1	7	0.3	0.7
Others	5	2	2	1	1	4	0	2	2	3	5	27	1.0	0.2
ASIA	122	14	20	33	28	41	37	62	48	44	37	486	17.9	0.8
China	20	2	5	2	6	7	7	5	5	9	7	75	2.8	0.7
Japan	24	4		3	4	4	4	3	6	3	4	59	2.2	0.4
Iran	0		2	6	2	5	6	10	8	6	7	52	1.9	0.8
South Korea	8		2	1	4	3	4	10	6	9	4	51	1.9	0.9
India	8	1	2	8	2	9	1	9	2	3	4	49	1.8	0.1
Taiwan	15	2	3	4	1	3	5	5	2	3	1	44	1.6	0.2
Others	47	5	6	9	9	10	10	20	19	11	10	156	5.8	0.8
EUROPE	159	20	26	25	32	31	40	40	44	44	37	498	18.4	1.0
Netherlands	20	5	4	5	5	6	11	6	9	6	5	82	3.0	0.6
U.K	16	5	3	3	4	7	3	7	7	13	7	75	2.8	0.7
Germany	16	4	4	5	4	5	5	6	1	3	10	63	2.3	-0.3
Finland	24	1	1	1	3		2	3	8	1	1	45	1.7	0.5
Sweden	16		1	1	2	4	2	5	6	3	2	42	1.5	0.8
Norway	11	1	4	1	1		3	3		3	2	29	1.1	0.1
France	9			1			4	1	6	1	2	24	0.9	0.6
Others	47	4	9	8	13	9	10	9	7	14	8	138	5.1	0.5
N. AMERICA	673	65	77	66	83	87	83	89	114	123	79	1539	56.8	0.9
U.S	632	63	71	60	79	85	77	83	107	110	71	1438	53.0	0.9
Canada	40	2	3	6	3	2	5	6	6	12	8	93	3.4	0.7
Others	1	0	3	0	1	0	1	0	1	1	0	8	0.3	-0.1
OCEANIA	13	3	5	5	4	5	9	10	11	12	6	83	3.1	0.9
Australia	12	2	3	5	4	4	8	9	10	11	6	74	2.7	1.0
Others	1	1	2	0	0	1	1	1	1	1	0	9	0.3	
S. AMERICA	11		4	2	1	2	5	2	5	4	4	40	1.5	0.6
Brazil	6		4	2	1	1	4	2	1		3	24	0.9	-0.2
Others	5	0	0	0	0	1	1	0	4	4	1	16	0.6	0.8
Total	989	104	138	133	152	174	177	208	229	237	170	2711	100.0	1.0

board can be easily displayed on Google Maps. The most influential country and the keywords are the US and health behavior. Readers are suggested to manipulate them on their own on Google Maps.

Many previous types of research[7–10] have inspected coauthor collaboration using social network analysis. Their results were similar to this study that dominant nations in science come from the U.S. and Europe.[21,22] We showed a novel method incorporating SNA with Google maps to explore the data of publication outputs on health behavior. It can be seen that visual representations provided to the reader are rare in literature. Traditionally, it is very hard to observe the association of two or more symptoms or ties together appeared in a network at a moment glance.

Journal authorship collaboration can be compared with each other using SNA on Google Maps. Such a network can be defined as a collaboration pattern which results are similar to the previous study.[4] Accordingly, the researchers have a high level of international coauthor collaboration on health behavior, which is consistent with the previous studies on investigating scientific collaboration of Iranian Psychology and Psychiatry Researchers.[23,24]

There are 1,084 papers with the keyword social network analysis in the paper title when searching Medline on December 21, 2017, in which two papers[25,26] incorporated MeSH into SNA to disclose relevant knowledge to readers. However, no such papers have incorporated Google maps as a dashboard.

Scientific publication is one of the objective measurements to evaluate the achievements of a medical specialty or discipline.[27] It is worth combining SNA and Google Maps to disclose knowledge and information to the readers for reference in the future.

Many algorithms and measures (or indicators) have been developed using SNA to graphically explore data.[7] This kind of author names should be identified for the bibliometric study. The BC is a way to examine any one with duplicate names through the link to Pubmed by clinking the bigger bubble on Google Maps which is never seen before in previous studies.

5 Limitations and Future study

The interpretation and generalization of the conclusions should be cautious. First, the data were extracted from Medline. It is worth noting that any generalization should be made in the similar fields of paper contents.

Second, although the data were extracted from Medline and were carefully dealt with in every linkage as correctly as possible, the originally downloaded contexts including some errors in symbols which might affect the resulting reports in this study may be present.

Third, there are many algorithms used for SNA. We merely applied community cluster and density with weighted degrees in Figures. Any changes made along with algorithm will present different pattern and inference making.

Fourth, the social network analysis is not subject to the Pajeck software we used in this study, Others such as Ucinet[28] and Gephi[29] are suggested to readers for use in the future study.

6 Conclusion

Social network analysis provides wide and deep insight into the relationships with the pattern of international author collaborations. If incorporated with Google Maps, the dashboard can release much more information regarding our interesting topics for us in academics. The research approach using the BC to identify the same author names can be applied to other bibliometric analyses in the future.

7 Competing interests

The authors declare that they have no competing interests.

8 Authors contributions

SH conceived and designed the study, TW performed the statistical analyses and were in charge of dealing with data. SB and TW helped design the study, collected information and interpreted data. CC monitored the research. All authors read and approved the final article.

References

[1] Haileamlak A. What Factors Affect Health Seeking Behavior? Ethiop J Health Sci, 2018,**28**(2):110.
https://doi.org/10.4314/ejhs.v28i2.1

[2] Bauer NS, Sullivan PD, Szczepaniak D, *et al*.Attention Deficit-Hyperactivity Disorder Group Visits Improve Parental Emotional Health and Perceptions of Child Behavior.J Dev Behav Pediatr, 2018 Jun 4. [Epub ahead of print]
https://doi.org/10.1097/DBP.0000000000000575

[3] Domingos p. A few useful things to know about machine learning. Communications of the ACM, 2012, **55**(10):78-87.
https://doi.org/10.1145/2347736.2347755

[4] Verhoef PC, Erfanmanesh, Walk N. Creating Value with Big Data Analytics: Making Smarter Marketing Decisions. London: Routledge, 2016.

[5] Power DJ. What is the ”true story” about data mining, beer and diapers? DSS News. 2017/3/20 available at
https://goo.gl/1FtGft

[6] Morris MA, Saboury B, Burkett B, *et al*. Reinventing Radiology: Big Data and the Future of Medical Imaging. J Thorac Imaging, 2018, **33**(1):4-16.
https://doi.org/10.1097/RTI.0000000000000311

[7] Sadoughi F, Valinejadi A, Shirazi MS, *et al*. Social Network Analysis of Iranian Researchers on Medical Parasitology: A 41 Year Co-Authorship Survey.Iran J Parasitol, 2016, **11**(2):204-212.

[8] Osareh F, Khademi R, Rostami MK, *et al*. Co-authorship Network Structure Analysis of Iranian Researchers scientific outputs from 1991 to 2013 based on the Social Science Citation Index (SSCI). Collnet J Scientometr Info Manag, 2014, **8**(2): 263-271.
https://doi.org/10.1080/09737766.2014.1015301

[9] Liu X, Bollen J, Nelson ML, *et al*. Coauthorship networks in the digital library research community. Info Process Manag, 2005, **41**(6): 1462-1480.
https://doi.org/10.1016/j.ipm.2005.03.012

[10] Shen L, Xiong B, Li W, *et al*. Visualizing Collaboration Characteristics and Topic Burst on International Mobile Health Research: Bibliometric Analysis.JMIR Mhealth Uhealth, 2018, **6**(6):e135.
https://doi.org/10.2196/mhealth.9581

[11] Dasgupta S, Vaughan AS, Kramer MR, *et al*. Use of a Google Map Tool Embedded in an Internet Survey Instrument: Is it a Valid and Reliable Alternative to Geocoded Address Data?JMIR Res Protoc, 2014, **3**(2):e24.
https://doi.org/10.2196/resprot.2946

[12] Kobayashi S, Fujioka T, Tanaka Y, *et al*. A geographical information system using the Google Map API for guidance to referral hospitals. J Med Syst, 2010, **34**(6):1157-1160.
https://doi.org/10.1007/s10916-009-9335-0

[13] Freeman LC. Centrality in social networks conceptual clarification. Soc Networks, 1979, **1**(3):215-239.

[14] Otte E, Rousseau R. Social network analysis: a powerful strategy, also for the information sciences. J Inform Sci, 2002, **28**(6):441-453.
https://doi.org/10.1177/016555150202800601

[15] Bright CF, Haynes EE, Patterson D, *et al*. The Value of Social Network Analysis for Evaluating Academic- Community Partnerships and Collaborations for Social Determinants of Health Research. Ethn Dis, 2017, **27**(Suppl 1):337-346.
https://doi.org/10.18865/ed.27.S1.337

[16] de Nooy W, Mrvar A, Batagelj V. Exploratory Social Network Analysis With Pajek: Revised and Expanded, 2nd edn. New York, NY: Cambridge University Press, 2011.
https://doi.org/10.1017/CBO9780511996368

[17] Phan TG, Beare R, Chen J, *et al*. Googling Service Boundaries for Endovascular Clot Retrieval Hub Hospitals in a Metropolitan Setting: Proof-of-Concept Study. Stroke, 2017, **48**(5):1353-1361.
https://doi.org/10.1161/STROKEAHA.116.015323

[18] Chien TW. Google Maps on health behavior for authors. 2018/7/1 available at
http://www.healthup.org.tw/gps/healthandbehavior.htm

[19] Chien TW. Google Maps on health behavior for author nations. 2018/7/1 available at
http://www.healthup.org.tw/gps/healthandbehaviornation.htm

[20] Chien TW. Google Maps on health behavior for MESH terns. 2018/7/1
http://www.healthup.org.tw/gps/healthandbehaviormesh.htm

[21] Leydesdorff L, Wagner C, Park HW, Adams J.International collaboration in science: the global map and the network. CoRR abs/1301.0801 (2013)

[22] Glnzel W, Schlemmer B. National research profiles in a changing Europe (19832003) An exploratory study of sectoral characteristics in the Triple Helix. Scientometrics, 2007, **70**(2):267-275.

[23] Erfanmanesh MA, Rohani VA, Basirian Jahromi R, *et al*. Investigating Scientific Collaboration of Iranian Psychology and Psychiatry Researchers. J Info Process Manag, 2013, **29**(1):137-163.

[24] Osareh F, Norouzi Chakoli A, *et al*. Co-authorship of Iranian researchers in science, social science, art and humanities citation indexes in the web of science between 2000 and 2006. J Info Sci Technol, 2010, **25**(4):573-595.

[25] Hu SK, Huang J, Hong WD, *et al*. The 50 Most-cited Articles in Gastroenterology and Hepatology from Mainland China.Pak J Med Sci,2017, **33**(1):215-220.
https://doi.org/10.12669/pjms.331.12286

[26] Coelho DH, Edelmayer LW, Fenton JE. A century of citation classics in otolaryngology-head and neck surgery journals revisited. Laryngoscope, 2014, **124**(6):1358-1362.
https://doi.org/10.1002/lary.24573

[27] Chang HT, Lin MH, Hwang IH, *et al*. Scientific publications in gastroenterology and hepatology in Taiwan: An analysis of Web of Science from 1993 to 2013.J Chin Med Assoc, 2017, **80**(2):80-85.
https://doi.org/10.1016/j.jcma.2016.06.006

[28] Borgatti SP, Everett MG, Freeman LC. Ucinet for Windows: Software for Social Network Analysis. Harvard, MA: Analytic Technologies 2002.

[29] Bastian M, Heymann S, Jacomy M. Gephi: an open source software for exploring and manipulating networks. International AAAI Conference on Weblogs and Social Media,2009.

Adv Health And Behavior, 2018, 1(1), 24−29
DOI: 10.25082/AHB.2018.01.005

RESEARCH ARTICLE

The most highly-cited authors who published papers on the topic of health behavior: A Bibliometric Analysis

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Abstract: Background: Health behavior (HB) is an action taken by a person who pursues good health and prevents illness. Health behavior, thus, reflects a person's health beliefs and attracts, particularly, on published papers in academics. However, who is the most influential author (MIA) with highly-cited papers on HB remains unknown. Objective: The purpose of this study is to apply the authorship-weighted scheme (AWS) developed by authors to select the MIA on HB using the visual displays on Google Maps. Methods: We obtained 1,116 abstracts published between 2012 and 2016 from Medline based on the keywords of (health [Title]) and (behavior [Title] or behavior [Title]) on September 22, 2018. The author names, countries/areas, and Pubmed paper IDs were recorded. The AWS was applied to (1) select the most productive authors (MPA) using social network analysis (SNA); (2) discover the MIA using h-indexes and author impact factors (AIF) dispersed on Google Maps, and (3) display the countries/areas distributed for the x-index in geography. Pajek software was performed to determine the partition categories of clusters. Results: We found that the MPA and MIA are Matthew K Nock (US) and Erika A Waters (US) for the MPA and MIA, respectively. All visual representations that are the form of a dashboard can be easily displayed on Google Maps. The most influential countries are the US (=19.03) and Australia (=6.46) with the highest x-indexes. Readers are suggested to manipulate them on their own on Google Maps. Conclusion: Many individual researchers achievements (IRA) were determined using h-index, AIF, x-index, or other bibliometric indices without quantifying author contributions. We demonstrated visualized representations on Google Maps using the AWS developed by authors to measure authors influences in a specific discipline. The research approach using the AWS to quantify the authors contributions can be applied to measure IRA in the future.

Keywords: authorship-weighted scheme, most productive author, most influential author, Google Maps, social network analysis, health behavior

1 Introduction

Health behavior (HB) is an action taken by a person to maintain, attain, or regain good health and to prevent illness.[1,2] Many papers were published in academics each year. The most productive author (MPA) has been selected by authors[2] on the topic of HB. However, the most highly-cited authors have not been discussed in the literature.

The h-index[3] is an author-level metric that attempts to measure both the productivity and citation impact of the publications of a scientist or scholar. Although the h-index can measure both the productivity and citation impact of the publications of a scientist, one of its shortcomings is the assumption of equal credits for all co-authors in an article.[4,5] Many studies[6–8] have been conducted to investigate individual researchers achievements (IRA) in a specific discipline. However, all or which ignored the co-author contributions unequal in an article byline.[5–9] Although many authors developed schemes for quantifying author contributions in the literature,[10–16] none had been successfully used so far in academics. A general authorship-weighted scheme (AWS) is thus required to develop for use in the empirical discipline.

Besides h-index,[3] the author impact factor (AIF)[17,18] and the x-index[19] are also plagued and criticized by scholars in bibliometric fields without

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considering the author contributions in a byline.

If we consider the contribution of the scientist in the publication, the weights of author contributions should be partitioned with real numbers (i.e., with decimal digits). How to apply the author weights to calculate h-index limited by the terms of integrals remains quite challenging and needs to solve. We are going to demonstrate the AWS for quantifying author contributions used on h-index, AIF, and x-index in this study.

For this purpose, we (1) develop a scheme for quantifying author contributions used for calculating the h-index for authors, (2) explore the most productive author(MPA) using AWS, (3) highlight the most influential authors (MIA) with highly cited papers in a disciple of HB, and (4) plot the countries/areas with highly cited x-index on Google Maps to show the most influential nations on HB.

2 Methods

2.1 Data Collection

By searching the PubMed database (Pubmed.org, PMC) maintained by the US National Library of Medicine, we used the keywords of (health [Title]) and (behavior [Title] or behavior [Title]) on September 22, 2018, and downloaded 1,116 articles published between 2012 and 2016. The inclusion criteria are all downloaded abstracts based on the type of Journal Article. Ethical approval was not necessary for this study because all the data were obtained from the Medline library on the Internet.

2.2 Social network analysis and Pajek software

Social network analysis (SNA)[20] was applied to explore the pattern of entities in a system using the software of Pajek.[21] In keeping with the Pajek guidelines, we defined an author (or paper keyword) as a node that is connected to other nodes through the edge (or say the relation). Usually, the weight between two nodes is defined by the number of connections.

Centrality is a vital index to analyze the network. Any individual or keyword lies in the center of the social network will determine its influence on the network and its speed to gain information.[22–24]

2.3 The AWS for quantifying coauthor contributions

The AWS was developed referring to the Rasch rating scale model[25] for quantifying author contributions as the Equation (1):

$$W_j = \frac{exp(\gamma_j)}{\sum\limits_{j-0}^{m} exp(\gamma_j)} = \frac{2.72^{\gamma_j}}{\sum\limits_{j-0}^{m} 2.72^{\gamma_j}} \tag{1}$$

The sum of author weights in a byline equals 1.0 when considering the number of m+1 authors with the last being the corresponding author, see the Equation (2), whereas W_j in Equation (1) denotes the weight for an author on the ordering of author j in the article byline. The power γ_j is an integer number from m to 0 in descending order.

The sum of author weights in a byline is defined as below:

$$\sum_{j-0}^{m} \frac{exp(\gamma_j)}{\sum\limits_{j-0}^{m} exp(\gamma_j)} \tag{2}$$

Accordingly, more importance is given to the first (= exp (m), primary) and the last (= exp (m-1), corresponding or supervisory) authors, while it is assumed that the others (the middle authors) have made smaller contributions.[26] In Equation (2), the smallest portion (= exp (0) = 1) is assigned to the last second author with the odds=1 as the basic reference.

2.4 A simple 5-year h-indexes and the AIFs

The AIF of an author A for a given the year (e.g, 2017) can be defined in Equation (3):

$$\begin{aligned} AIF(SMA) = (&\sum Cited\ papers\ based\ on \times \\ &W_j\ in\ a\ givenyear\ and\ the\ proceeding\ 5\ yrs)/ \\ &(Citable\ papers\ \times W_j\ in\ the\ given\ 5\ yrs) \end{aligned} \tag{3}$$

A total number of 4,857 authors were collected for calculating their h-indexes, x-indexes, and AIFs in 2017 based on citable papers in PMC since 2012. All indices were located on dashboards using SNA and Google Maps.

The rule for applying author weights to calculate h-index is defined as below:
$h = cm + (h-1)/10\ for\ h\text{-}core\ if\ max(ci) < 1$ and $h = h + the\ decimal\ if\ max(ci) \geqslant 1$, where cm=the maximal proportional citation weights (i.e., max (ci) across all ci for an individual authors. The possible scenarios of AWS and the rules for calculating the h-index with real numbers were illustrated in Table 1.

Table 1. Using AWS to quantify the author contributions and to comput h-index

A: Quantifying the author contributions with scenarios

# of author	1	2	3	4	5	6	7	8	9	Ratio
Threshold	0	1	2	3	4	5	6	7	8	
The first	1	0.7	0.7	0.6	0.6	0.6	0.6	0.6	0.6	2.72
The 2nd		0.3	0.2	0.2	0.2	0.2	0.2	0.2	0.2	2.72
The 3rd			0.1	0.1	0.1	0.1	0.1	0.1	0.1	2.72
The 4th				0	0	0	0	0	0	2.72
The 5th					0	0	0	0	0	2.72
The 6th						0	0	0	0	2.72
The 7th							0	0	0	2.72
The 8th								0	0	2.72
The 9th									0	
Sum	1	1	1	1	1	1	1	1	1	

B: Computing h-index using real nature numbers

Scenario	Script, cm=max(ci), k at h-core	h-index	1	2	3	4	5	6	7
1	=cm+(h-1)/10 if cm<1,0.5+(2-1)/10	0.6	0.5	0.3	0.1				
2	=h(k)=h index	4	10	10	10	10			
3	=h index	1	100	1					
4	=h index	1	1	1	1	1	1	1	
5	=h + decimal if cm >=1	1.6	11	1					
6	=h + decimal if cm >=1, 3+ 0.3	3.3	4.6	4	3.3	2.7			
7	=cm+(h-1)/10 if cm<1,0.9+(5-1)/10	1.3	0.9	0.8	0.7	0.6	0.5	0.4	0.3
8	=h + decimal if cm >=1. 2+0.4	2.4	8	3.4	2				
9	=h index	5	10	9	8	7	6	5	4
10	=h index	3	3	3	3	3	3	3	3

2.5 The pattern of author collaboration on health behavior

Three diagrams were plotted on Google Maps through the ways of (1) selecting the most productive authors (MPA) using SNA; (2) discovering the MIA using h-indexes and author impact factors (AIF) dispersed on Google Maps; and (3)displaying the countries/areas distributed for the x-index in geography. The bigger bubble means the most pivotal role played as a bridge in the network if the BC algorithm is performed. The wider line indicates, the stronger relations between the two (i.e., the nation or the author). Clusters separated by the algorithm of the partition communities are filled with bubbles in different colors. The study flowchart is displayed in Figure 1.

3 Results

3.1 The most productive and influential author

The MPA and MIA on the topic of HB are Matthew K Nock (US) and Erika A Waters (US), respectively, shown in Figure 2 and Figure 3. We can see the representatives with the most number of centrality degrees in each cluster. Interested readers are recommended to scan the QR-codes on Figures to see the details of information for authors on Google Maps. For instance, clicking the term of publication can be redirected to the PMC to show the publications of the specific author of interest.

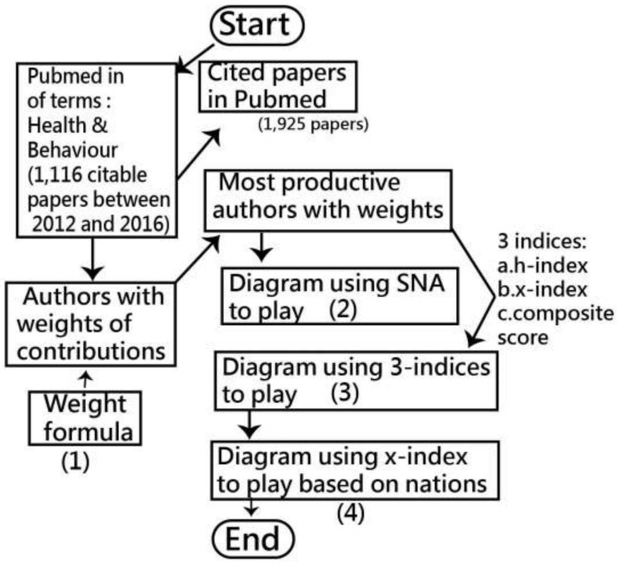

Figure 1. Study flowchart including one table and three Figures

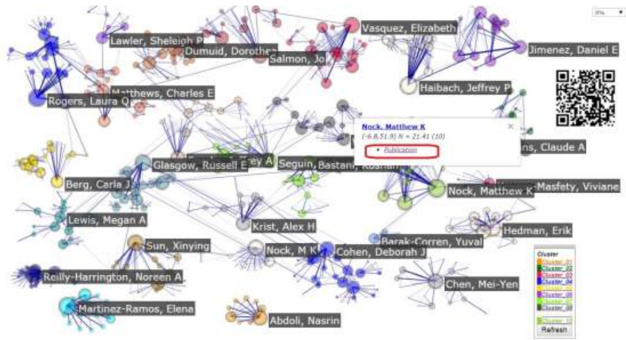

Figure 2. Dispersion of coauthor clusters based on weighted contributions

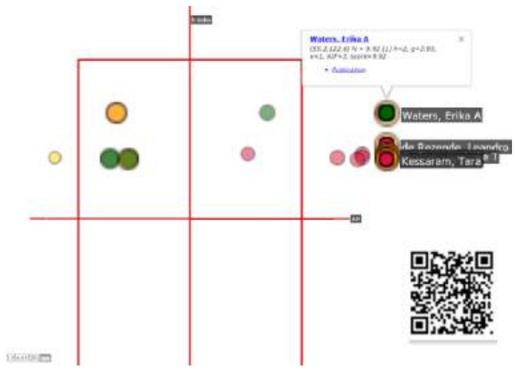

Figure 3. Dispersion of authors h-index and AIF

3.2 The most influential nations on HB

The mostly influential nation is the U.S., see Figure 4. The calculation of the algorithm is to obtain the x-index for each country/area through the way of ranking the individual author contributions to each cited paper by nations in the descending order. The maximal geometric rectangle was selected by multiplying the ascending integer number of cited papers and the descending real nature number of proportional cited weights.[19] The x-index is the root of the above-mentioned geometric rectangle which is similar and related to h-index according to the study.[19]

Figure 4. Dispersion of h-indexes for countries/areas

4 Discussion

This study found that the MPA and MIA are Matthew K Nock (US) and Erika A Waters (US) for the MPA and MIA, respectively. All visual representations that are the form of a dashboard can be easily displayed on Google Maps. The most influential countries are the US (=19.03) and Australia (=6.46) with the highest x-indexes.

Many previous types of research[20,22,23] have inspected coauthor collaboration using social network analysis. Their results were similar to this study. The difference is that we applied the AWS to quantify the author contributions in an article byline in comparison to the previous articles merely assuming all authors are equal in contributions and credits.

We showed a novel AWS method for quantifying author contributions that is a totally general model fully congruent with the category probability theory based on the Rasch rating scale model (RSM).[25] We can adjust the parameters(i.e., the base and the power) to accommodate many types of scenarios in the empirical discipline. Hence, Vavryuks combined weighted scheme[10] (or the harmonic credits[27]) is a special case of the general AWS in Eq. 2.

Traditionally, it is tough to observe the association of two or more symptoms or ties together appeared in a network at a momentary glance. The representatives in each cluster are determined by three factors: (1) the number of coauthors in a byline; the more coauthors will generate more proportional contributions in a network; (2) the number of publication outputs; and (3) the ordering of author names in a byline. The method we used in this study is superior to the previous ones[20,22,23] without considering the author contribution unequal to each other.

There are 1,084 papers with the keyword social network analysis in the paper title when searching Medline on December 21, 2017,[1,2] in which two papers[28,29] incorporated MeSH into SNA to disclose relevant knowledge to readers. However, no such papers have incorporated Google maps as a dashboard as we did in this study.

Scientific publication is one of the objective measurements to evaluate the achievements of a medical specialty or discipline.[30] It is worth combining SNA and Google Maps to disclose knowledge and information to the readers for reference in the future. Many algorithms and measures (or indicators) have been developed using SNA to graphically explore data.[31] This kind of author names should be identified and quantified for the bibliometric study. The duplicate names should be cautious when dealing with the used in discovering the MPA and MIA in the future.

5 Limitations and Future study

The interpretation and generalization of the conclusions should be cautious. First, the data were extracted from Medline. It is worth noting that any generalization should be made in the similar fields of paper contents.

Second, although the data were extracted from Medline and were carefully dealt with in every linkage as correctly as possible, the originally downloaded contexts including some errors in symbols which might affect the resulting reports in this study may be present.

Third, there are many algorithms used for SNA. We merely applied community cluster and density with weighted degrees in Figures. Any changes made along with algorithm will present different pattern and inference making.

Fourth, the social network analysis is not subject to the Pajeck software we used in this study, others such as Ucinet[32] and Gephi[33] are suggested to readers for use in the future study.

6 Conclusion

Many individual researchers achievements (IRA) were determined using h-index, AIF, x-index, or other bibliometric indices without quantifying author contributions. We demonstrated visualized representations on Google Maps using the AWS developed by authors to measure authors influences in a specific discipline. The research approach using the AWS to quantify the authors contributions can be applied to measure IRA in the future.

7 List of abbreviations

AIF: author impact factors
AWS: authorship-weighted scheme
HB: Health behavior
IRA: individual researchers achievements
MIA: most influential author
MPA: most productive author
PMC: Pubmed Center
SNA: Social network analysis

8 Competing interests

The authors declare that they have no competing interests.

9 Authors contributions

CF conceived and designed the study, TW performed the statistical analyses and were in charge of dealing with data. CC and TW helped design the study, collected information and interpreted data. WC monitored the research. All authors read and approved the final article.

References

[1] Haileamlak A. What Factors Affect Health Seeking Behavior? Ethiop J Health Sci, 2018, **28**(2): 110. https://doi.org/10.4314/ejhs.v28i2.1

[2] Chen SH, Chien TW, Su SB, *et al*. A dashboard on Google Maps to show the most influential author on the topic of health behavior: A Bibliometric Analysis. Adv Health And Behavior, 2018, **1**(1): 1-7. https://doi.org/10.25082/AHB.2018.01.004

[3] Hirsch JE. An index to quantify an individuals scientific research output. Proc. Natl. Acad. Sci., 2005, **15**(102): 16569-16572. https://doi.org/10.1073/pnas.0507655102

[4] Etersen AM, Fortunato S, Pan RK, *et al*. Reputation and impact in academic careers. Proc Natl Acad Sci USA, 2014, **111**(43): 15316-15321. https://doi.org/10.1073/pnas.1323111111

[5] Sekercioglu CH. Quantifying coauthor contributions. Science, 2008, **322**(5900): 371. https://doi.org/10.1126/science.322.5900.371a

[6] Yuen J. Comparison of Impact Factor, Eigenfactor Metrics, and SCImago Journal Rank Indicator and h-index for Neurosurgical and Spinal Surgical Journals. World Neurosurg, 2018, (119): e328-e337. https://doi.org/10.1016/j.wneu.2018.07.144

[7] Post A, Li AY, Dai JB, *et al*. c-index and Subindices of the h-index: New Variants of the h-index to Account for Variations in Author Contribution. Send to Cureus, 2018, **10**(5): e2629. https://doi.org/10.7759/cureus.2629

[8] Ashfaq A, Kalagara R and Wasif N. H-index and academic rank in general surgery and surgical specialties in the United States. J Surg Res., 2018, (229): 108-113. https://doi.org/10.1016/j.jss.2018.03.059

[9] Jayant SV and V-index. A fairer index to quantify an individual's research output capacity". BMJ, 2005, **311**(728): 1339c1340c.

[10] Vavryuk V. Fair ranking of researchers and research teams. PLoS One, 2018, **13**(4): e0195509. https://doi.org/10.1371/journal.pone.0195509

[11] Batista PD, Campiteli MG, Kinouchi O, *et al*. Is it possible to compare researchers with different scientific interests? Scientometrics. 2006, **68**(1): 179189. https://arxiv.org/ftp/physics/papers/0509/0509048.pdf

[12] Lindsey D. Production and citation measures in the sociology of science: The problem of multiple authorship. Soc Stud Sci, 1980, **10**(2): 145162. https://doi.org/10.1177/030631278001000202

[13] Lindsey D. Further evidence for adjusting for multiple authorship. Scientometrics, 1982, **4**(5): 389395. https://doi.org/10.1007/BF02135124

[14] Egghe L, Rousseau R and Van Hooydonk G. Methods for accrediting publications to authors or countries: Consequences for evaluation studies. J Am Soc Inform Sci, 2000, **51**(2): 145157. https://doi.org/10.1002/(SICI)1097-4571(2000)51:2⟨145::AID-ASI6⟩3.0.CO;2-9

[15] Tscharntke T, Hochberg ME, Rand TA, *et al*. Author sequence and credit for contributions in multiauthored publications. PLOS Biology, 2007, **5**(1): e18. https://doi.org/10.1371/journal.pbio.0050018

[16] Waltman L. A review of the literature on citation impact indicators. Journal of Informetrics, 2015, **10**(2): 365-391. https://doi.org/10.1016/j.joi.2016.02.007

[17] Pan RK and Fortunato S. Author Impact Factor: tracking the dynamics of individual scientific impact. Sci Rep, 2014, (4): 4880. https://doi.org/10.1038/srep04880

[18] Lippi G and Mattiuzzi C. Scientist impact factor (SIF): a new metric for improving scientists' evaluation? Ann Transl Med, 2017, **5**(15): 303. https://doi.org/10.21037/atm.2017.06.24

[19] Fenner T, Harris M, Levene M, *et al*. A novel bibliometric index with a simple geometric interpretation. PLoS One, 2018, **13**(7): 19.e0200098. https://doi.org/10.1371/journal.pone.0200098

[20] Bright CF, Haynes EE, Patterson D, *et al*. The Value of Social Network Analysis for Evaluating Academic-Community Partnerships and Collaborations for Social Determinants of Health Research. Ethn Dis, 2017, (Suppl 1): 337-346. https://doi.org/10.18865/ed.27.S1.337

[21] De Nooy W, Mrvar A and Batagelj V. Exploratory Social Network Analysis With Pajek: Revised and Expanded, 2nd edn. New York, NY: Cambridge University Press, 2011.
https://doi.org/10.1017/9781108565691

[22] Otte E and Rousseau R. Social network analysis: a powerful strategy, also for the information sciences. J Inform Sci., 2002, **28**(6): 441453.
https://doi.org/10.1177/016555150202800601

[23] Bright CF, Haynes EE, Patterson D, *et al*. The Value of Social Network Analysis for Evaluating Academic-Community Partnerships and Collaborations for Social Determinants of Health Research. Ethn Dis., 2017, **27**(Suppl 1): 337-346.
https://doi.org/10.18865/ed.27.S1.337

[24] Phan TG, Beare R, Chen J, *et al*. Googling Service Boundaries for Endovascular Clot Retrieval Hub Hospitals in a Metropolitan Setting: Proof-of-Concept Study. Stroke, 2017, **48**(5): 1353-1361.
https://doi.org/10.1161/STROKEAHA.116.015323

[25] Andrich D. Relationships between the Thurstone and Rasch approaches to item scaling. Applied Psychological Measurement, 1978, **2**(3): 451-462.
https://doi.org/10.1177/014662167800200319

[26] Lindsey D. Further evidence for adjusting for multiple authorship. Scientometrics, 1982, **4**(5): 389395.
https://doi.org/10.1007/BF02135124

[27] Hagen NT. Harmonic allocation of authorship credit: source-level correction of bibliometric bias assures accurate publication and citation analysis. PLoS One, 2008, **3**(12): e402.
https://doi.org/10.1371/journal.pone.0004021

[28] Hu SK, Huang J, Hong WD, *et al*. The 50 Most-cited Articles in Gastroenterology and Hepatology from Mainland China. Pak J Med Sci., 2017, **33**(1): 215-220.
https://doi.org/10.12669/pjms.331.12286

[29] Coelho DH, Edelmayer LW and Fenton JE. A century of citation classics in otolaryngology-head and neck surgery journals revisited. Laryngoscope, 2014. **124**(6): 1358-1362.
https://doi.org/10.1002/lary.24573

[30] Chang HT, Lin MH, Hwang IH, *et al*. Scientific publications in gastroenterology and hepatology in Taiwan: An analysis of Web of Science from 1993 to 2013. J Chin Med Assoc, 2017, **80**(2): 80-85.
https://doi.org/10.1016/j.jcma.2016.06.006

[31] Sadoughi F, Valinejadi A and Shirazi MS, *et al*. Social Network Analysis of Iranian Researchers on Medical Parasitology: A 41 Year Co-Authorship Survey. Iran J Parasitol, 2016, **11**(2): 204-212.
http://ijpa.tums.ac.ir/index.php/ijpa/article/view/1060

[32] Borgatti SP, Everett MG and Freeman LC. Ucinet for Windows: Software for Social Network Analysis. Harvard, MA: Analytic Technologies, 2002.

[33] Bastian M, Heymann S and Jacomy M. Gephi: an open source software for exploring and manipulating networks. International AAAI Conference on Weblogs and Social Media, 2009.
http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.172.7704&rep=rep1&type=pdf