

Original Research Article

Pathway analysis to characterize the relationships between healthcare access and healthcare visits in the United States using the health information national trends survey

Qinglin Hu^{1,2*}, Xiaobing Li³, Mercedes M. Morales-Alemán^{1,2}

¹The Institute for Rural Health Research, University of Alabama, Tuscaloosa, Alabama, USA

²Department of Community Medicine and Population Health, University of Alabama, Tuscaloosa, Alabama, USA

³The Alabama Transportation Institute, University of Alabama, Tuscaloosa, Alabama, USA

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*Correspondence:

Dr. Qinglin Hu,
E-mail: Qhu10@ua.edu

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ABSTRACT

Background: Americans had fewer healthcare visits compared to their counterparts in other developed countries. The lack of regular check-ups can contribute to worsening health conditions. Insurance coverage, access to transportation to healthcare services, and having accessed health information via the internet are known to be associated with frequency of healthcare visits. However, there is limited literature detailing the direct and indirect influences of these variables on frequency of patients' healthcare visits. We aimed to understand the interactive relationship between insurance coverage, access to transportation to healthcare services, and having accessed health information via the internet on frequency of patient healthcare visits.

Methods: We used data from the 2018 Health Information National Trends Survey (N=3504), the only survey year providing the source for information on insurance coverage, access to transportation to healthcare services, and having accessed health information via the internet. We used descriptive statistics, random parameter binary logistic regression, and pathway analysis to describe and analyze the associations between these determinants of healthcare access and healthcare visits.

Results: Results indicated that access to transportation to healthcare services (18.32%) and having insurance coverage (27.89%) were directly associated with healthcare visit frequency whereas the association between having accessed health information via the internet and reporting a healthcare visit, compare to the former two, was weakened (10.87%). Residential area (rural/urban), health conditions, age, race/ethnicity, employment status were directly associated with visit frequency whereas income status and education level were associated with healthcare visits indirectly through insurance.

Conclusions: Better understanding interactive relationships between healthcare access determinants will be key to the development of healthcare access interventions aimed at reducing healthcare disparities.

Keywords: Healthcare access, Healthcare visits, Pathway analysis, Healthcare disparities

INTRODUCTION

Access to healthcare is crucial to managing chronic health conditions, preventing disease, and ameliorating health disparities.¹⁻⁴ One of the key goals of National Healthy People 2030 is improving population health by increasing access to comprehensive, high-quality healthcare

services.⁵ However, barriers to healthcare access are still a top concern for policy makers and health professionals in the United States.⁶⁻⁸ The mechanisms underlying access to healthcare are complex and often need to be evaluated in ways that capture how they are interrelated.⁹ In general, healthcare access has been conceptualized in terms of affordability, the physical accessibility, and the

availability of services. Although useful to an extent, this mode of understanding healthcare accessibility can miss the bidirectional nature of determinants of healthcare access. One of the aims of this study was to explore these relationships in a new and more comprehensive way using pathway analysis.

Many Americans face significant challenges in accessing healthcare services as a result of social determinants of health, that is the conditions in people's environments that affect their quality of life and health.⁵ US Census reports show that about 1 in 10 people in the United States have no health insurance.¹⁰ Americans without health insurance are less likely to have a regular health provider, and are less able to afford the health treatments that they need.^{6,9} Additionally, in 2017 the American Hospital Association (AHA) reported that approximately 3.6 million Americans face challenges obtaining medical care due to lack of transportation.¹¹

Patients without access to reliable transportation are more likely to miss appointments, delay care or medication use and, as a result, incur increased health expenditures and worse health outcomes.⁷ Recent data show that older and lower income patients are less likely to benefit from online health information, resulting in internet skills-related health disparities.^{12,13} Although previous research found that internet skills and education level are associated with use of various sources of health information, such as telehealth, social media or online health support groups, the majority of patients with inadequate access to high-speed internet are often unable to efficiently gather information about their health conditions and treatment options, make online appointments, communicate with their providers, and access their patient records. Despite this, few studies have characterized the effects of these variables on healthcare access using pathway analysis.

Several studies have found that individuals who are older, report having a lower level of education, experience a lower SES, have fewer internet skills, and are of Hispanic background experience more barriers to healthcare that, in turn, lead to unmet healthcare needs and worse health outcomes, especially during the COVID-19 crisis.^{1,6-9,12-21} Therefore, there is a need to explore determinants of healthcare visits and their interactive effects among these populations in national samples. In reviewing the extant literature, we found that pathway analysis studies have examined the relationships between various health-related factors (e.g., emitted pollutant, community environment, socioeconomic status and occupational class, etc.) and health issues (e.g., cancer, chronic diseases, mental health, etc.). However, those studies have largely focused on investigating the pathways between specific determinants and diseases.²²⁻²⁹ For instance, Li et al found that limited walking environment and unhealthy air quality was associated with participants' reduced willingness to engage in physical activities. This, in turn, worsened health conditions of patients with chronic diseases. Other studies have focused on examining the

effects of individual determinants (e.g., insurance coverage, transportation access or internet resources) on healthcare services.^{1,6-9,12-21} However, to our knowledge, few studies have empirically examined the relationship between having insurance coverage, transportation to healthcare services, and accessing health information via internet resources to healthcare and their integrated direct and indirect marginal effects on healthcare visits.

We examined the direct and indirect effects of these three access determinants to health services on frequency of provider healthcare visits with the aim of: examining the significance of each of the determinants on access to health services, exploring a pathway linkage between three access determinants and healthcare visits, examining how all three access determinants, as a whole, impact health outcomes.

METHODS

Data and sample

We used the 2018 Health Information National Trends Survey (HINTS). HINTS is a nationally representative household interview cross-sectional survey of US adults aged ≥ 18 years who are noninstitutionalized civilians. The sampling frame consisted of a two-stage design where the first stage involved selecting a random sample of residential addresses, and the second stage included selecting one adult within each household. The 2018 HINTS dataset was the only year to include questions on insurance coverage, transportation to healthcare services, and accessing health information via internet. Our target sample was participants with valid responses for these 3 variables.

A total of 3504 respondents were included for descriptive analyses and an analytic sample of 3468 with complete responses for all measures was used in the regression models (e.g., binary logistic regression, ordered logistic regression). To estimate the values for the U.S. population, we applied sampling weights based on the Horvitz-Thompson estimator (jackknife with 50 replicates) to this study, which account for the biases introduced through planned over-sampling and differential response rates. Missing values in predictor variables accounted for 15% of the analyzed sample. To reduce the potential bias due to excluding the missing variables, each predictor variable with missing values was treated as a separate category in the logistic regression model. This methodology can be viewed and downloaded from the National Cancer Institute (NCI) Health Information National Trends Survey (HINTS) website.³⁰ The HINTS data was granted exempted status by the Internal Review Board (IRB) of the NCI's Office of Human Subjects Research and by the IRB of the organization that administers the survey, Westat. The current analysis was exempted from review by the IRB of the University of Alabama.

Measures

Outcome variables

In this study, the outcome variable of interest was frequency of visits to healthcare providers. It was captured with the following survey question: “In the past 12 months, not counting times you went to an emergency room, how many times did you go to a doctor?” Originally, the responses were classified into 8 categories: Missing data (Not Ascertained), None, 1 time, 2 times, 3 times, 4 times, 5-9 times, 10 or more times. The first category represented the missing data and was removed for modeling purposes (e.g., 36 observations with missing information were removed) and subsequent analyses in the study. The rest of the categories were reclassified into 5 groups as 0 time, 1-2 times, 3-4 times, 5-9 times, 10 or more times. This response variable was coded as 0, 1, 2, 3, and 4, with an ordinal nature in the ordered logistic regression model. In addition to healthcare visit frequency, insurance was considered as another response variable in the binary logistic regression model to capture the indirect effects of transportation to access and accessing health information on health visit frequency through the pathway analysis. In this study, we collapsed insurance into a binary variable (1—with insurance; 0—without insurance). We hypothesized that insurance coverage was a prerequisite condition for patients who had more frequent physical healthcare visits.

Key independent variables

The key independent variables of interest in this study were seeking health information via internet and having

transportation to healthcare facilities when needed. Seeking health information via internet was captured through the survey question, “In the past 12 months have you used a computer, smart phone, or other electronic means to look for health or medical information for yourself?” Responses were recoded as a binary variable. Transportation access to healthcare provider was captured through the survey question – “Do you have someone to take you to the doctor if you need it?” Responses were recoded as an ordinal variable.

Other independent variables

In addition, other independent variables that were included in the modeling process were: self-reported general health condition, urban or rural area, gender, age, race, employment status, marital status, education level, household income, and ever diagnosed with cancers. More detailed descriptions of the above-mentioned dependent variables and the potential explanatory variables can be found in Table 1. In total, a sample size of 3,468 responses were used in subsequent models for further analysis.

RESULTS

Descriptive summary

The analytical sample included 3504 adult respondents, representing 249,489,772 individuals.³⁰

Table 1 presents the descriptive statistics of the variables. Approximately 15% (14.6%) of respondents had not visited a healthcare provider in the past 12 months.

Table 1: Descriptive statistics of the response and explanatory variables used in this study (n=3,504).

Variable description		Frequency	Proportion (%)
General health status (response variable)	Fair or poor	546	15.74
	Good	1203	34.69
	Excellent or very good	1685	48.59
	Unknown	34	0.98
Frequency of doctor visits in the past 12 months	None	507	14.62
	1-2 times	1208	34.83
	3-4 times	967	27.88
	5-9 times	499	14.39
	10 or more times	287	8.28
Insurance	No	183	5.28
	Yes	3285	94.72
Internet access	No	749	21.60
	Yes	2719	78.40
Transport to visit health providers	Never or rarely	402	11.47
	Sometimes	414	11.82
	Often or always	2603	74.29
	Don't know	85	2.43
Income	\$0 ~\$34,999	1090	31.43
	\$35,000 ~ \$74,999	1034	29.83
	\$75,000 ~ \$99,999	399	11.51
	\$100,000 or more	840	24.22
	Don't know	105	3.03

Continued.

Variable description		Frequency	Proportion (%)
Employment status	Employed	1708	49.25
	Unemployed	128	3.69
	Others	1566	45.16
	Don't know	66	1.90
Education level	High school or less	1148	33.10
	Some college	812	23.41
	College graduate	915	26.38
	Postgraduate	593	17.10
Age (in years)	18 ~ 34	412	11.88
	35 ~ 49	667	19.23
	50 ~ 64	1133	32.67
	65 and above	1256	36.22
Gender	Male	1405	40.51
	Female	2063	59.49
Race	White	2541	73.27
	Black or African American	581	16.75
	Asian	155	4.47
	Others	191	5.51
Marital Status	Married or Living as married	1764	50.87
	Others	1704	49.13
Urban or rural area	Urban in metro area	2983	86.01
	Urban in non-metro area	443	12.77
	Rural in non-metro area	42	1.21
Seeking health information in the past 12 months via internet	No	1133	32.33
	Yes	2313	66.01
	Unknown	58	1.66
Ever had cancer	No	2877	82.96
	Yes	591	17.04

Table 2: Factors associated with insurance based on binary logistic regression model.

Y1 = Having insurance			
Variable		β	ME
Constant		0.665***	---
Household income (Base: \$0 - 34,999)	\$35,000 - 74,999	0.408***	1.69%
	\$75,000 - 99,999	1.287***	5.34%
	\$100,000 and over	1.063***	4.41%
	Unknown	0.007	0.03%
Education (Base: high school or less)	Some college	0.703***	2.91%
	College graduate	0.304*	1.26%
	Postgraduate	0.890***	3.69%
Employment status (Base: employed)	Unemployed	-0.831***	-3.45%
	Others (e.g., retired)	0.245	1.01%
	Unknown	-0.626	-2.60%
Age (Base: 18-34)	35-49	0.641***	2.66%
	50-64	0.560***	2.32%
	65 and over	1.780***	7.38%
Internet access	Yes	0.621***	2.58%
Scale parameters (standard deviation) for random parameters	Some college	1.776***	---
	Age (35-49)	1.717***	---
	Internet access	1.125***	---
Summary statistics	Number of observations		3,468
	Log likelihood at zero L(0)		-716.443
	Log likelihood at convergence L(β)		-615.873
	McFadden Pseudo R-squared		0.002

Notes: *** = significant at 99% level; ** = significant at 95% level; and * = significant at 90% level; Shaded cells represent random parameter estimations; “---” represents not available; Normal distribution is used for the random parameters.

Table 3: Factors associated with frequency to visit healthcare providers based on ordered logistic regression model.

Variables		Coef.	Std. Err.	Marginal effects				
				None	1-2 times	3-4 times	5-9 times	10 or more times
Constant		0.133	0.204	---	---	---	---	---
Insurance (Yes vs. No)		1.222***	0.139	-19.09%	-8.79%	14.21%	8.98%	4.70%
Self-rated health condition (Base: poor or fair)	Good	-0.649***	0.093	7.51%	8.56%	-6.34%	-6.12%	-3.61%
	Very good or excellent	-1.330***	0.095	14.76%	17.32%	-11.09%	12.78%	-8.21%
	Unknown	-0.676**	0.305	9.19%	7.18%	-7.66%	-5.64%	-3.06%
Internet access (Yes vs. No)		0.405***	0.086	-4.72%	-5.35%	4.06%	3.80%	2.20%
Help with transport (Base: never or rarely get help with transport)	Sometimes get help with transport	0.333***	0.127	-3.23%	-5.03%	2.55%	3.48%	2.24%
	Always or often get help with transport	0.437***	0.098	-5.07%	-5.81%	4.35%	4.12%	2.40%
	Unknown	0.251	0.224	-2.45%	-3.79%	1.95%	2.61%	1.67%
Household income (Base: \$0 - 34,999)	\$35,000 - 74,999	0.054	0.083	-0.57%	-0.78%	0.49%	0.54%	0.33%
	\$75,000 - 99,999	0.221*	0.116	-2.22%	-3.29%	1.81%	2.27%	1.43%
	\$100,000 and over	0.112	0.100	-1.17%	-1.62%	0.98%	1.12%	0.69%
	Unknown	-0.095	0.193	1.05%	1.32%	-0.90%	-0.92%	-0.55%
Employment status (Base: employed)	Unemployed	0.306*	0.162	-2.94%	-4.65%	2.30%	3.21%	2.08%
	Others (e.g., retired)	0.389***	0.081	-4.11%	-5.59%	3.43%	3.88%	2.38%
	Unknown	0.081	0.232	-0.84%	-1.18%	0.70%	0.82%	0.50%
Education (Base: high school or less)	Some college	-0.028	0.088	0.30%	0.39%	-0.25%	-0.27%	-0.16%
	College graduate	0.266***	0.090	-2.71%	-3.91%	2.23%	2.70%	1.68%
	Postgraduate	0.434***	0.106	-4.17%	-6.57%	3.23%	4.55%	2.96%
Age (Base: 18-34)	35-49	-0.055	0.112	0.60%	0.78%	-0.51%	-0.54%	-0.33%
	50-64	0.183*	0.105	-1.91%	-2.66%	1.60%	1.84%	1.13%
	65 and over	0.371***	0.117	-3.82%	-5.41%	3.15%	3.75%	2.33%
Gender (Base: male)	Female	0.362***	0.064	-3.97%	-5.05%	3.38%	3.53%	2.11%
Race (Base: white)	Black or African American	0.007	0.088	-0.07%	-0.10%	0.06%	0.07%	0.04%
	Asian	-0.439***	0.148	5.44%	5.41%	-4.68%	-3.94%	-2.22%
	Others	-0.061	0.136	0.67%	0.87%	-0.57%	-0.60%	-0.36%
Rural (Base: urban in metro area)	Urban in non-metro area	0.156*	0.093	-1.60%	-2.30%	1.32%	1.59%	0.99%
	Rural in non-metro area	-0.455	0.302	5.73%	5.49%	-4.93%	-4.04%	-2.26%
Ever had cancer (Base: no)	Yes	0.552***	0.088	-5.15%	-8.41%	3.82%	5.84%	3.90%
Scale parameters for distribution of random parameters	Insurance	0.082***	0.015	---	---	---	---	---
	Good self-rated health condition	0.118**	0.052	---	---	---	---	---
	Other employment status	0.322***	0.046	---	---	---	---	---

Continued.

Variables	Coef.	Std. Err.	Marginal effects				
			None	1-2 times	3-4 times	5-9 times	10 or more times
Cut point 1	1.950***	0.053	---	---	---	---	---
Cut point 2	3.373***	0.063	---	---	---	---	---
Cut point 3	4.659***	0.081	---	---	---	---	---
Summary statistics	Number of observations		3,468				
	Log likelihood at zero L(0)		-5166.418				
	Log likelihood at convergence L(β)		-4893.774				
	Pseudo R2		0.053				
	AIC		9857.5				

Notes: Coef.=coefficient; Std. Err.=standard error; *p<0.1; **p<0.05; ***p<0.01; AIC=Akaike information criterion; "----" represents not available.

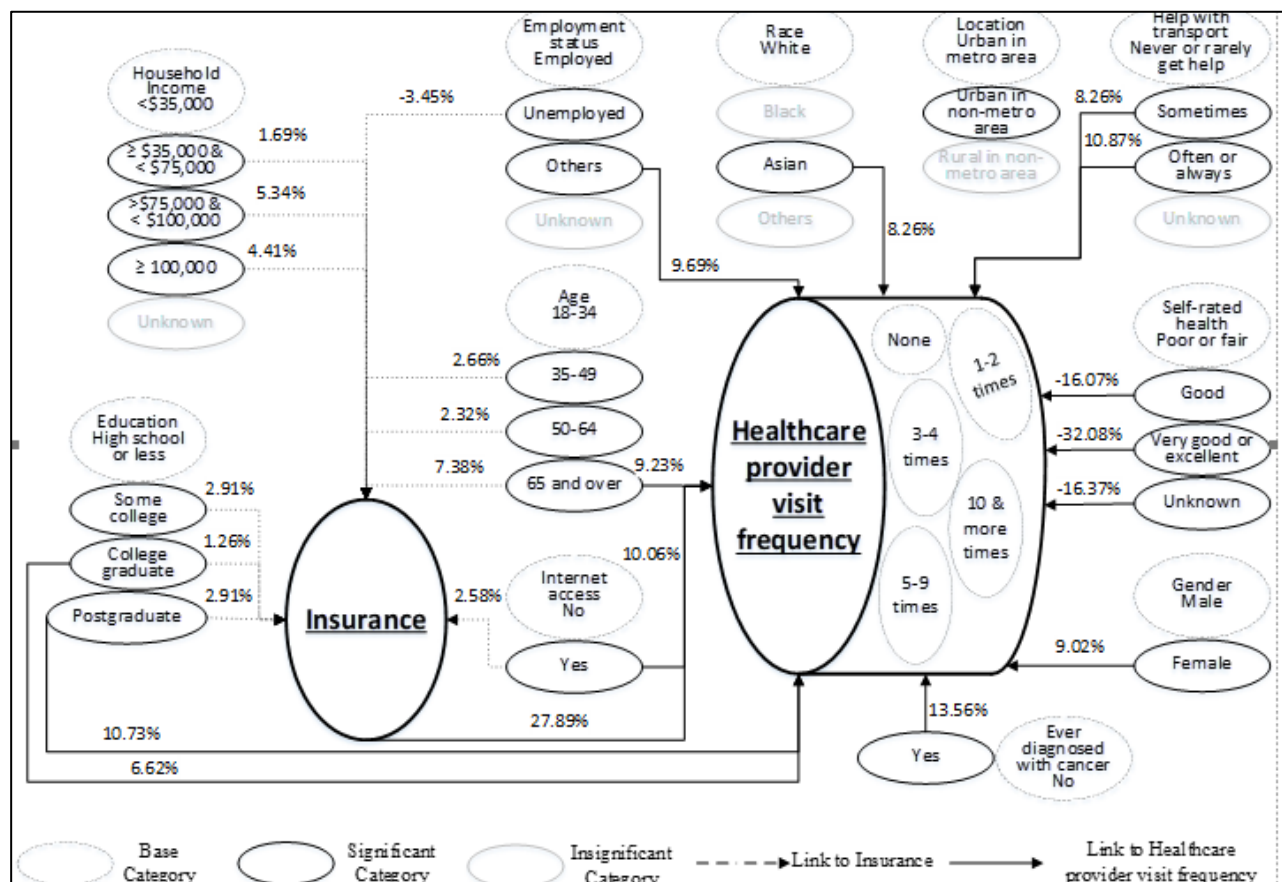


Figure 1: Flowchart of pathway analysis on healthcare access.

Only 5.28% of the respondents did not have health insurance. Almost twenty-two percent (21.6%) of those surveyed reported that they did not have internet access. Approximately 66% of all the surveyed respondents reported seeking health information for themselves in the past 12 months using electronic means (e.g., computer, smart phone). Approximately 74% of respondents reported that when they needed transport to their healthcare providers, they were able to access it while 11.5% reported that they sometimes had transport and 11.8% respondents said they rarely or never had transport to see the doctor. Most respondents (about 86%) reported living in an urban setting. Almost 60% of respondents

were female, and 36.2% of them were 65 years old or older. The percentage of employed respondents was 49.3%, and 50.9% were married or living as married. Approximately 33% reported a high school-level of education or less, 73.3% were white, and 31.4% of them had an income less than \$35,000.

Model selection

The two of the response variables were: health insurance – coded as a binary variable; frequency of visits to healthcare providers – coded as an ordinal variable with 5 levels. Conventionally, regression models are used to

examine the relationships between outcome variables and selected independent variables.³¹ For example, with respect to dependent variable, binary logistic regression is often used for health insurance and ordered logistic regression model for frequency to visit healthcare providers. Methodologically speaking, if conventional fixed regression models are built, the relationship between a response variable and independent variable is the same across all observations. While in fact, such a relationship could vary from one observation to another (e.g., the magnitude of correlation can be stronger in one case and weaker in another). Those changes can be captured by introducing the random parameter model and allowing the estimated coefficients to vary across the observations to account for the unobserved heterogeneity due to the unavailability of the unobserved data. The key advantage of random parameter models over fixed parameters models is their power to account for the unobserved heterogeneity embedded in the data for the surveyed respondents.³² Specifically, the outcomes (i.e., healthcare visit frequency) may not just be affected by the factors that are collected in the dataset; but also, by many other factors that are not collected in the dataset (i.e., people's daily changing schedule, emotions, cultural beliefs, etc.). Thus, random parameters were incorporated into the two selected regression models. For example, random parameter binary logistic regression model (RPBLM) was used to estimate the relationship between the insurance variable and various selected factors. Random parameter ordered logistic regression model (RPOLRM) was adopted to model the frequency to visit healthcare providers. Both models will be explained in detail in later sections.

Insurance-based pathway analysis

One key outcome from regression models is the marginal effect. It means the change of the outcome variable when one independent changes from its mean (or base category) to the desired category while other variables are kept at their means (or base category). In the RPOLRM, marginal effects are direct marginal effects of those selected variables in this model. The degree to which respondents reported healthcare provider visit frequency was heavily dependent on whether they had healthcare insurance. Thus, the RPBLM model provides additional indirect marginal effects through the healthcare insurance mediator. In other words, some social determinants may not directly impact the healthcare visit frequency. This study investigated the indirect marginal effects of three access determinants to health service on healthcare visits. For example, income status may not directly impact the healthcare visit frequency, but through insurance, it may have an indirect marginal effect. Pathway analysis provides additional combined marginal effects on the healthcare provider visit frequency based on the direct and indirect relationships with the associated factors. More mathematical formulations of pathway analysis can be found in authors' other work.^{26,28,29}

Model I

Random parameter binary logistic regression modeling for health insurance

The RPBLM is estimated to predict the probability of having insurance given a set of social determinants. Table 2 presents the results of the RPBLM model. The results indicated that, compared to respondents who had lower household income (i.e., \$0 - 34,999), those who had higher income (i.e., \$35,000 and higher) were more likely to have insurance. Similarly, those who had higher education (e.g., some college or higher), were aged 35 or older, and had internet access to health information were more likely to have insurance. In contrast, compared with the employed, the unemployed were significantly less likely to have insurance. The RPBLM also indicated that some of the variable categories held significant variations of estimations (e.g., some college education, aged between 35-49 years old, and internet access). Specifically, the normal distribution of these parameters indicated that 65.4% of the respondents who had some college education had insurance. As for younger adults (i.e., aged between 35-49 years old) compared to people aged 18-34, 64.6% of them were more likely to have insurance. These results suggest that unobserved heterogeneity exists in the model and should be considered to improve model performance.

Model II

Random parameter ordered logistic regression model (insurance-based) for frequency to visit healthcare providers

The random parameter OLR model (RPOLRM) is estimated to account for the unobserved heterogeneity. Table 3 presents the modeling results for frequency of provider healthcare visits using RPOLRM based on selected variables in Table 1. Non-significant variables were not included in the final model. The modeling results show that transport to see a doctor and internet access for healthcare information did have significant impacts on respondents' frequency of provider healthcare visits. For example, compared to respondents who reported that they never or rarely had transport to doctor when needed, those who sometimes, often, or always had transport were more likely to report a higher frequency of healthcare provider visits (e.g., 3 or more times in the past 12 months). Additionally, compared to those who did not have internet access for health information, those who access for health information were also more likely to have reported a visit to healthcare providers 3 or more times in the past 12 months. These outcomes seem to suggest that limited transportation to health providers and internet inaccessibility may decrease the likelihood of visiting healthcare providers.

Other explanatory variables were also observed to be significantly associated with the frequency of visits to

healthcare providers in the past 12 months. Particularly, respondents with insurance were more likely to report healthcare provider visits. Respondents with good, very good, or excellent health self-rated health conditions were less likely to visit healthcare providers. Additionally, for other social determinants, if the respondents had a higher income (e.g., \$75,000 - 99,999), other employment status (e.g., retired, disabled, student, homemaker), or higher education (e.g., college graduate, postgraduate) and were older adults (e.g., aged 50 or older), female, ever diagnosed with cancer, they were more likely to visit healthcare providers more frequently. Figure 1 presents a map of pathway linkage among these variables (the next section covers this in more detail). Furthermore, the estimated random parameters (i.e., insurance, good self-rated health condition, other employment status) indicate that the estimations varied significantly between respondents. The RPOLRM provides additional implications to account for the unobserved heterogeneity when estimating the correlations.

The results further illustrate that when indirect marginal effects are added through the pathway analysis, the total marginal effects will likely change (Figure 1). For example, respondents who had sought healthcare information via internet, lived in urban areas, were female, had a higher level of education, and had access to transportation to see providers were even more likely to visit healthcare providers frequently (i.e., 3 or more times) compared to their counterparts. In addition, respondents who had household incomes that were more than \$35,000 were more likely to have insurance which indirectly led to a greater visiting frequency.

DISCUSSION

This study sought to understand the direct and indirect influences of insurance coverage, access to transportation to healthcare services, and having accessed health information via the internet on patients' healthcare visits. Our model first examined the association between these three healthcare access determinants. Our hypothesis was that insurance coverage acts as a prerequisite condition for patients who had more frequent physical healthcare visits. The results of this study found that individuals who had higher incomes, reported higher levels education (i.e., college or above), were younger, and having accessed health information via the internet were more likely to report having health insurance, which led to more healthcare visits. These findings are aligned with Kaplan et al's results.³³ However, the results also showed the presence of unobserved heterogeneity which needed to be considered to improve model performance. In our subsequent model, we incorporated the random parameter ordered logistic regression to examine the unobserved heterogeneity of the healthcare visit determinants. Previous works have focused on the influence of each determinant on healthcare visit individually. Anderson et al and Zuckerman et al found that insured adults were more likely to frequently visit their doctors.^{34,35} In a study

by Arcury et al they found that respondents who had family or friends who could provide transportation had 1.58 times more visits than those who did not.³⁶ Other studies have focused on telehealth visits, demonstrating that patients with telehealth visits may proportionally substitute their office visits; however, this tendency depends on their medical conditions, disease types, technology access and sociodemographic characteristics.^{37,38} Unfortunately, the scholarly findings are limited, and we have found no additional studies that address the mutual or interactive effects of those three determinants on healthcare visits. Our study attempts to fill this gap. Our results show that insured patients with transportation capacity and having internet access are significantly more likely to report higher healthcare visit frequency. Since little is known on the association between different questions provided by the survey, it is difficult to investigate the varying associations between physical and virtual healthcare visit. Future studies are needed to further examine the applicability of telehealth visit and office visits.

In addition, our study was designed to apply a pathway analysis to investigate how these three determinants interact with each other and how they impact healthcare visits with both direct and indirect marginal effects. The study findings support the hypothesis that access to transportation to healthcare services and having accessed health information via the internet can have both direct and indirect relationships with visit frequency to healthcare providers through the pathway of insurance. Particularly, for the variables of accessing health information via the internet and postgraduate education, the results indicated that the indirect marginal effects further enlarged the direct marginal effects, meaning the magnitude of total marginal effects of those two factors on frequency to visit healthcare providers was greater than what had been estimated in the model I.

Using the integrated 2018 survey data from the Health Information National Trends Survey (HINTS), we believe our findings provide a more nuanced method to approach healthcare access research. First, our study examined the significance of each determinant on access to health services. Second, this study provided enhanced knowledge of the way the determinants interacted, which may help researchers toward a better understanding of the overall mechanisms underlying healthcare access. Third, our study showed that all three access determinants played an important role in reducing the risk of poor health outcomes. By modeling the interrelationships between these variables, we were able to shed light on the associations between our constructs of interest and health outcome. Better understanding these relationships can, in turn, provide new lenses through which to develop public health efforts and remove barriers to care. Finally, our research findings may provide valuable thoughts for policy makers as well as health professionals to improve our current system and better serve prospective patients

who are older, with lower education level and socioeconomic status.

Limitations

Similar to other observational studies, this study also has limitations because of the nature of sampling design. First, the survey design for HINTS is cross-sectional in nature. Although we observed associations between demographic characteristics with the patients' healthcare visit frequency, definitive conclusions cannot support a causal inference. Second, the 2018 HINTS was the only survey year providing, from a random sample of the US population, the source for information on insurance coverage, access to transportation to healthcare services, and having accessed health information via the internet. A multiyear cross-sectional study would allow improved data to identify the associations between these three determinants and healthcare visit. Third, for the transportation to healthcare services, due to limitation of the survey information, this study only reflects the patients or respondents who were transported by someone else. Therefore, it is hard to say whether patients or respondents use public transportations or owned vehicle would have the same results. Fourth, this study only focuses on the physical healthcare visit, the virtual healthcare visits (telehealth visit) are not in our study scope. Lastly, the HINTS response rate was approximately 32%, which may lead to selection and estimation bias. We suggest that local or micro-level studies are needed to validate these findings, and to provide a better, detailed interpretation of findings for decision making and policy use.

CONCLUSION

Although several limitations exist, the findings of the present analysis remain valid and relevant: Insurance coverage, along with the availability of transportation to healthcare services, and accessing health information via the internet, can play a significant role in promoting and maintaining health conditions, preventing and eliminating disease, and ameliorating health disparities. Patients with varying sociodemographic characteristics may encounter different barriers to healthcare access which may lead to worse health outcomes. Better understanding the direct and indirect associations between three access determinants, with related interactive effects on patients' decisions to healthcare visits, could provide a viable framework for health officials to prioritize the implementation of specific interventions on target groups. Effective interventions and intentional, data-driven allocations on existing health resources could largely improve healthcare access among groups who have healthcare needs and expedite the pace of achieving the goal of the National Healthy People 2030.

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