Received: 25 July 2023 | Revised: 29 October 2023 | Accepted: 27 November 2023

DOI: 10.1002/ajim.23556

RESEARCH ARTICLE

AMERICAN JOURNAL OF INDUSTRIAL MEDICINE WILEY

Exploring the characteristics and health outcomes of working from home: Analysis of 2021 California Health Interview Survey data

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Abstract

Background: Working from home (WFH) may affect health behaviors and mental health. The coronavirus disease-2019 (COVID-19) pandemic saw many US employees transition to WFH, which has persisted in various job sectors and significantly impacted employees. However, its effects on health outcomes have remained unclear. We aimed to explore the characteristics and health outcomes of, and health-related differences between, WFH and not-WFH groups.

Methods: Using the 2021 California Health Interview Survey data, we analyzed health behaviors (smoking, alcohol consumption, and fruit-related nutrition) and the mental health status of 12,438 individuals using descriptive statistics, Pearson's χ^2 test, and regressions.

Results: A total of 39% were WFH and 61% were not-WFH. Overall, the WFH group had worse health behaviors and mental health than the not-WFH group. Age was associated with smoking in both groups (WFH: $b = 0.37$; not-WFH: $b = 0.35$), but with fruit-related nutrition only in the WFH group. Household income and occupation were associated with alcohol consumption in both groups. Age (WFH: $b = -1.58$; not-WFH: $b = -1.39$), household income (WFH: $b = -0.75$; not-WFH: $b = -0.34$), and job duration (WFH: $b = -0.34$; not-WFH: $b = -0.40$) were associated with mental health in both groups; those who were younger and had lower household incomes and job durations had worse mental health.

Conclusion: Health management is a clear necessity for the WFH group. Irrespective of WFH status, young workers with shorter than 5 years' job duration reported mental distress, highlighting a need for distress assessment and management for the young workforce.

KEYWORDS

California Health Interview Survey, COVID-19, employee, health behavior, mental health, worker, working from home

1 | INTRODUCTION

Although working from home (WFH) can offer benefits such as an improved work–life balance and promotion of health due to increased time flexibility,[1] it can also lead to an increase in sedentary behaviors and mental health issues due to a lack of social support and emotional exhaustion.[2] The coronavirus disease-2019 (COVID-19) pandemic has posed a significant obstacle to individual adherence to healthy behaviors, adding to the ongoing debate about the benefits and drawbacks of WFH.[3] WFH during the pandemic has led to decreases in mental health (e.g., depression) and overall healthy behaviors in workers, manifesting as reduced physical activity[4] and unhealthy eating habits.[5] For example, the abrupt work setting transition during the pandemic made it difficult for Polish adults to balance remote work and housework, which in turn led to challenges in anger management.[6]

During the pandemic, much of the US workforce transitioned to WFH. The 2021 Business Response Survey on the Coronavirus Pandemic reported that 31% of establishments increased employees' WFH opportunities by late 2020.[7] This transition has persisted in certain occupation sectors such as information and educational services, in which >50% of establishments saw an increase in WFH among their employees.[8] In addition to the United States, large data sets from other countries have shown the effects of WFH on populations around the world. For example, a population-based, South Korean Working Conditions Survey revealed that WFH among white-collar wage employees was associated with increases in anxiety, fatigue, and physical pain.[9] Even though it is clear that WFH during the pandemic significantly impacted the American workforce and their health behaviors, studies exploring the health of WFH workers using large data sets such as state-level or national data have remained lacking.

To address this research gap, we used the publicly available 2021 California Health Interview Survey (CHIS) data to understand the characteristics and health outcomes of individuals who work from home. The study has three aims: (1) describe the characteristics and health outcomes of individuals belonging to WFH and not-WFH groups; (2) identify variables associated with WFH or not-WFH and that affect health behaviors and mental health as an exploratory aim; and (3) explore differences in the health outcomes of both groups.

2 | MATERIALS AND METHODS

2.1 | CHIS data

The CHIS is one of the largest ongoing state health surveys in the United States, covering broad health topics and recording information on at least 20,000 individuals every year since its initiation in 2001. Data are continuously obtained through web and telephone surveys. This longitudinal data includes the use of and access to health care, health insurance, health conditions and behaviors, mental health, public program participation such as food stamps, housing, income and employment, climate change, food, gun violence, and adverse childhood experiences. The CHIS not only collects data on individual-level health and influencing factors but also addresses social justice issues such as including immigrant health, intimate partner violence, and discrimination. These variables are repeatedly measured every year to track significant shifts over time, and new emerging concerns such as those related to COVID-19 are added to the survey each year. The strengths of the CHIS include its ability to capture differences in racial and ethnic subgroups and underserved communities; and randomization of the sample ensures that it represents the diverse population of this large US state. The official website[10] offers options to download deidentified data in several forms and on a variety of topics. Data are published every 1–2 years.

2.2 | Methods

We used the 2021 CHIS public data set (N = 24,453). Based on the 2021 CHIS data (adult survey) public use file dictionary,[11–14] we excluded data on people who were looking for a job (n = 1303) or were unemployed (n = 9493), and data that could not be classified by the National Institute for Occupational Safety and Health Industry and Occupation Computerized Coding System (n = 1219). Thus, the final sample size for this study was 12,438 individuals split into WFH and not-WFH groups. Demographic and biological measures such as age, sex, race, and body index mass (BMI) were included. The work-related variables including working status (part-time, full-time, other employes) and main industry or occupation were also recorded. Fourteen main industries were selected: (1) agriculture, forestry, fishing, hunting, and mining; (2) arts, entertainment, recreation, accommodation, and food services; (3) construction; (4) educational services, health care, social assistance; (5) finance and insurance, real estate, rental, and leasing; (6) information; (7) manufacturing; (8) military; (9) other services, except public administration; (10) professional, scientific, and management; (11) public administration; (12) retail trade; (13) transportation, warehousing, and utilities, and (14) wholesale trade. In addition, 13 occupations were chosen: (1) computer, engineering, and science; (2) construction and extraction; (3) education, legal, community service, arts, and media; (4) farming, fishing, and forestry; (5) healthcare practitioners and technical; (6) installation, maintenance, and repair; (7) management, business, and financial; (8) military specific; (9) office and administrative support; (10) production; (11) sales and related occupations; (12) service; and (13) transportation and material moving.

2.2.1 | Dependent variables

Two health outcomes were considered: health behaviors and mental health. First outcome variable, health behaviors, included three variables: (1) smoking, with categories of "currently smokes (score = 2)," "quit smoking (score = 1)," and "never smoked regularly (score = 0);" (2) alcohol consumption, inferred from the question "How long has it been since you

last drank an alcoholic beverage?" and categories of "within the past 30 days (score = 3)," "more than 30 days ago, but within the past 12 months (score = 2)," "more than 12 months ago (score = 1)," and "never had an alcoholic beverage (score = 0);" (3) fruit-related nutrition, categorized as "number of times fruit was eaten in the past month" and "number of times fruit is eaten per week." For the smoking and alcohol variables, a score of 0 indicated a nonsmoker and someone who had never consumed alcohol, respectively. In contrast, a higher score indicated recent alcohol consumption (score = 3) and status as a current smoker (score = 2).

Second outcome variable, mental health, was measured using the Kessler 6-item (K6) Psychological Distress questionnaire.[15,16] The K6 is a brief, valid, and globally accepted scale that helps to identify community-based serious mental illness.[15,16] The K6 records feelings (nervous, hopeless, restless or fidgety, so depressed that nothing could cheer you up, everything is an effort, and worthless) during the 30 days preceding assessment. The responses for each feeling were 0 = *none of the time*, 1 = *a little of the time*, 2 = *some of the time*, 3 = *most of the time*, and 4 = *all of the time*. The score is calculated as a sum of these six items and can range from 0 to 24. A higher score indicates more severe distress.[15,16]

We used the survey data analytic method in Stata v18.0[17] for all analyses after accounting for the sample weighting. This allowed us to generate estimates for the entire Californian population (final weight variable: rakedw0),[14,18] control for other potential biases, and explain the sample selection likelihood. We attempted to reduce the error in variance estimates using strata codes (variables: tsvarstr and tsvrunit), but those variables were only applicable to confidential data. Thus, our use of the public data set limited our ability to account for the complex sample design of the CHIS.[18] To achieve aim 1, descriptive statistics and Pearson's χ^2 test in bivariate manner were implemented. To address aims 2 and 3, ordinal and linear regressions were applied.

3 | RESULTS

Among the 12,438 individuals analyzed, 39% (n = 4,795) were WFH and 61% (n = 7643) were not-WFH (Table 1). Overall, the majority of the participants were highly educated (some college and above), married, white, between normal and overweight BMI, early career (<5 years of working experience), working full time (≥21 h/week), and working in the "educational services, health care, social assistance" sector.

Sex, age, educational status, marital status, race, annual total household income, and BMI differed significantly between the WFH and not-WFH groups (all $p < 0.05$). All of the work-related variables (i.e., main industry, main occupation, working status, and job duration at main job) were also significantly different between the two groups (all $p < 0.01$). The majority of those in the WFH group were aged 30–39 years (27%), had high annual household incomes (>$150,000; 44%), and worked in the occupation sector of "computer, engineering and science" (25%). In the not-WFH group, the majority were aged 50–64 years (28%), had an annual household income of $50,000–$99,999 (28%), and worked in the "service" sector (21%) (Table 1). In addition, the not-WFH group had better overall health outcomes than the WFH group (Table 1). In the not-WFH group, more people had either never consumed or had not consumed alcohol for long durations ([not-WFH] mean score = 2.15; [WFH] mean score = 2.45; a higher score indicated recent alcohol consumption), had higher levels of fruit-related nutrition ([not-WFH] number of times fruit was eaten in the past month: mean = 36.39 times; number of times fruit is eaten per week: mean = 8.46 times; [WFH] number of times fruit was eaten in the past month: mean = 33.65 times; number of times fruit is eaten per week: mean = 7.82 times), and experienced less mental distress ([not-WFH] mean score = 5.88; [WFH] mean score = 7.43; a higher score indicated more severe distress). In contrast, the WFH group had more non-smokers ([not-WFH] mean score = 0.31; [WFH] mean score = 0.26; a higher score indicated status as a current smoker).

As shown in Table 2, ordinal logistic regression was applied to analyze smoking and alcohol consumption, and linear regression was applied to assess fruit-related nutrition and mental health. As two individuals did not answer the mental health assessment, mental health was evaluated for 12,436 individuals in all the regressions to achieve aims 2 and 3. Health behaviors were analyzed using data from 12,438 individuals. To identify the best model and associated variables affecting health behaviors and mental health during the COVID-19 pandemic, we included four variables with correlations >0.30 in the regression (i.e., age, annual total household income, occupation, and job duration at main job) to find the potential key covariate. More variables were associated in WFH (Table 2): age was associated with all health outcomes, except for alcohol consumption, in the WFH group.

Specifically, age was associated with smoking in both groups (WFH: $F = 20.61$, $p < 0.001$; not-WFH: $F = 23.30$, $p < 0.001$), and occupation was associated with smoking in only the WFH group. Household income and occupation were associated with alcohol consumption in both groups (WFH: $F = 4.75$, $p < 0.001$; not-WFH: $F = 13.61$, $p < 0.001$), whereas age was associated with alcohol consumption only in the not-WFH group. Age was also associated with fruit-related nutrition only in the WFH group (number of times fruit was eaten in the past month [WFH: $F = 3.33$, $p < 0.05$; not-WFH: F = 6.00, $p < 0.001$] and number of times fruit is eaten per week [WFH: $F = 3.30$, $p < 0.05$; not-WFH: $F = 6.05$, $p < 0.001$]). Age, household income, and job duration showed negative relationships with mental health in both groups (WFH: $F = 83.33$, $p < 0.001$; not-WFH: $F = 140.85$, $p < 0.001$), whereas occupation had a negative relationship with mental health only in the WFH group. In summary, the health outcomes for the WFH group had more significantly associated variables than the not-WFH group. In addition, occupation was associated with alcohol consumption (WFH: $b = -0.05$; not-WFH: $b = -0.03$) and job duration was associated with mental health (WFH: $b = -0.34$; not-WFH: $b = -0.40$) in both groups (Table 2).

As presented in Table 3, regression analyses showed significant differences in health behaviors and mental health between the WHF and not-WFH groups (all $p < 0.05$). Barring smoking, the overall health outcomes were better for those in the not-WFH group (all $p < 0.05$).

TABLE 1 Sociodemographic characteristics of survey respondents (N = 12,438).

Variable	WFH at any point during the COVID-19 pandemic (n = 4,795)	Not-WFH (n = 7643)	p Value
Sex**			
Female	50%	56%	<0.001
Male	50%	44%	
Age**			
18–29 years	22%	23%	<0.001
30–39 years	27%	20%	
40–49 years	22%	21%	
50–64 years	25%	28%	
65+ years	5%	8%	
Educational status**			
<High school	2%	16%	<0.001
High school	6%	23%	
Some college	13%	23%	
College degree or above	79%	38%	
Marital status*			
Married	54%	51%	0.02
Never married	24%	28%	
Others	22%	21%	
Race**			
African American	5%	6%	<0.001
American Indian/Alaska Native	1%	1%	
Asian	18%	13%	
Latino	14%	29%	
Multiple race	11%	15%	
White	51%	36%	
Annual total household income**			
0–19,999	4%	9%	<0.001
20,000–49,999	9%	23%	
50,000–99,999	23%	28%	
100,000–149,999	20%	17%	
150,000–over 180,000	44%	23%	
Body mass index**			
Underweight 0–18.49	2%	2%	<0.001
Normal 18.5–24.99	40%	32%	
Overweight 25–29.99	33%	36%	
Obese 30+	25%	30%	
Main industry**			
Agriculture, forestry, fishing, hunting, mining	0%	2%	<0.001

TABLE 1 (Continued)

Variable	WFH at any point during the COVID-19 pandemic (n = 4,795)	Not-WFH (n = 7643)	p Value
Arts, entertainment, recreation, accommodation, food services	3%	10%	
Construction	2%	6%	
Educational services, health care, social assistance	31%	22%	
Finance and insurance, real estate, rental, leasing	7%	4%	
Information	5%	2%	
Manufacturing	8%	9%	
Military	1%	1%	
Other services, except public administration	3%	5%	
Professional, scientific, management	25%	14%	
Public administration	8%	5%	
Retail trade	4%	11%	
Transportation, warehousing, and utilities (TWU)	2%	7%	
Wholesale trade	1%	2%	
Main occupation**			
Computer, engineering, and science	25%	7%	<0.001
Construction and extraction	0%	5%	
Education, legal, community service, arts, and media	24%	8%	
Farming, fishing, and forestry	0%	1%	
Healthcare practitioners and technical	2%	8%	
Installation, maintenance, and repair	1%	3%	
Management, business, and financial	23%	12%	
Military specific	0%	1%	
Office and administrative support	14%	12%	
Production	2%	6%	
Sales and related occupations	5%	9%	
Service	3%	21%	
Transportation and material moving	1%	7%	
Working status**			
Part-time (0–20 h/week)	9%	15%	<0.001
Full-time (21+ hours/week)	91%	84%	
Other employed	0%	1%	
Job duration at main job*			
0–4.99 years	50%	48%	0.006

(Continues)

TABLE 1 (Continued)

Variable	WFH at any point during the COVID-19 pandemic (n = 4,795)	Not-WFH (n = 7643)	p Value
5–9.99 years	20%	18%	
10–19.99 years	18%	19%	
20+ years	12%	15%	

	WFH			Not-WFH		
		95% CI			95% CI	
Category	Mean [SE]	Lower	Upper	Mean [SE]	Lower	Upper
Health outcomes						
Smoking	0.26 [0.01]	0.23	0.28	0.31 [0.01]	0.29	0.34
Alcohol consumption	2.45 [0.02]	2.41	2.49	2.15 [0.02]	2.11	2.20
Number of times fruit was eaten in the past month	33.65 [0.69]	32.30	34.99	36.39 [0.96]	34.51	38.28
Number of times fruit is eaten per week	7.82 [0.16]	7.50	8.13	8.46 [0.22]	8.02	8.89
Mental health	7.43 [0.14]	7.16	7.70	5.88 [0.12]	5.65	6.11

Note: 0% means less than 0.5%. Main industry and main occupation variables were coded with the help of the National Institute for Occupational Safety and Health Industry and Occupation Computerized Coding System (NIOCCS). NIOCCS is a web-based system that classifies industry and occupation responses into standardized codes that match the US Census 2010 industry and occupation classification scheme. Each percentage shows the proportion of the entire population (WFH and not-WFH).

Abbreviations: CI, confidential interval; SE, standard error; WFH, working from home.

$^{*}p < 0.05$; $^{**}p < 0.001$.

Not-WFH showed a negative relationship with alcohol consumption ($F = 7.35$, $p < 0.05$) and mental health ($F = 72.56$, $p < 0.001$), and a positive relationship with fruit-related nutrition (number of times fruit was eaten in the past month [$F = 5.39$, $p < 0.05$] and number of times fruit is eaten per week [$F = 5.42$, $p < 0.05$]). In other words, those in the not-WFH group were more likely to not consume alcohol or not have consumed alcohol for long durations ($b = -0.32$), have better fruit-related nutrition (number of times fruit was eaten in the past month: $b = 2.74$ and number of times fruit is eaten per week: $b = 0.64$), and report less mental distress ($b = -1.56$) than those in the WFH group. In summary, most of health outcomes in WFH group were worse than not-WFH.

4 | DISCUSSION

WFH is not a new or emerging concept. Home-based employment existed even in the 1980s and was considered to foster equality in employment in the face of various restrictions (e.g., disabilities).[19] The COVID-19 pandemic accelerated the WFH transition and changed the context of need for this work setting. The findings of our study supported Bloom's policy brief,[20] which stated that WFH was dominant in specific occupation sectors that relied on managing staff or working with technologies such as computers. In the brief, only 51% participants could avail WFH options and most of those in a not-WFH setting were essential service workers.[20] This trend was also reflected in our findings. Essential service workers cannot do their jobs without being physically present at their workplaces, either due to the nature of their job tasks or the requirement for specific work conditions (e.g., meeting customers). Bloom[20] also reported that workers with higher levels of education and income were more likely to work from home, which align with our findings. Many studies have examined the productivity of WFH settings from an economic perspective.[21,22] As the increase in WFH during the COVID-19 pandemic has been sustained in several occupations,[7,20] this work setting can be considered as impacting our lives both now and in the postpandemic future. Although some studies have reported partial changes in health both positively and negatively,[23,24] not enough studies have been conducted on the physical and mental health impacts of WFH. This is likely due to the complexity of analyzing the combination of individual, interpersonal, and organizational factors needed to compare WFH and not-WFH settings.

Overall, in our study, individuals in the WFH group had worse health behaviors and mental health than those in the not-WFH group. Only a few studies have compared health outcomes between WFH and not-WFH settings.[25,26] Fukushima et al.[25] addressed sedentary behavior and physical activity and found more sedentary time and less physical activity in a WFH group than in a not-WFH group. Due to data limitations, we could not obtain results in support of these findings. However, we did observe results that were similar in context, wherein the overall health of those in the WFH group was worse than those in the not-WFH group. Previous studies of employment changes that included WFH have reported health concerns.[23,27,28] For example, Ekpanyaskul and Padungtod[23]

TABLE 2 Regression results for WFH and not-WFH groups with associated variables (N = 12,438).

Health outcomes	Associated variables	WFH			Not-WFH		
		b	SE	*t*	*b*	SE	t
Smoking[a]	Age	0.37	0.05	7.40**	0.35	0.04	8.76**
	Annual total household income	−0.03	0.05	−0.72	−0.05	0.04	−1.48
	Occupation	0.05	0.20	2.59*	0.03	0.01	1.96
	Job duration	−0.02	0.05	−0.35	−0.10	0.04	−2.40*
Alcohol consumption[a]	Age	0.06	0.05	1.20	0.11	0.04	2.96*
	Annual total household income	0.17	0.05	3.34*	0.16	0.03	4.59**
	Occupation	−0.05	0.02	−2.31*	−0.03	0.01	−2.05*
	Job duration	−0.05	0.05	−0.89	0.02	0.04	0.55
Number of times fruit was eaten in the past month[b]	(constant)	30.30	3.69	8.21**	34.33	4.60	7.46**
	Age	2.49	0.70	3.55**	1.47	0.81	1.81
	Annual total household income	−0.45	0.71	−0.63	−1.58	0.95	−1.66
	Occupation	0.09	0.32	0.29	0.002	0.25	0.01
	Job duration	−0.92	0.69	−1.32	1.51	0.88	1.72
Number of times fruit is eaten per week[b]	(constant)	7.05	0.86	8.17**	7.98	1.07	7.47**
	Age	0.58	0.16	3.53**	0.35	0.19	1.83
	Annual total household income	−0.11	0.17	−0.65	−0.37	0.22	−1.67
	Occupation	0.02	0.07	0.28	−0.001	0.06	−0.02
	Job duration	−0.21	0.16	−1.31	0.35	0.20	1.71
Mental health[b,c]	(constant)	15.08	0.64	23.42**	12.84	0.41	31.07**
	Age	−1.58	0.12	−13.38**	−1.39	0.08	−17.00**
	Annual total household income	−0.75	0.12	−6.08**	−0.34	0.07	−4.56**
	Occupation	0.03	0.05	0.54	−0.14	0.03	−4.82**
	Job duration	−0.34	0.11	−2.95*	−0.40	0.08	−5.31**

Note: Only variables with correlations >0.30 were included in the regression analyses: age, annual total house income, occupation, and job duration at main job.

Abbreviations: CI, confidential interval; SE, standard error; WFH, working from home.

[a]Ordinal logistic regression was applied.

[b]Linear regression was applied.

[c]Sample size of 12,436.

*p <0.05; **p <0.001.

reported weight control issues, musculoskeletal pain, and anxiety in those in the WFH group. Additionally, McDowell et al.[28] showed that those either belonging to a WFH group or who had lost their jobs showed increased sedentary and screen time. They also reported potential physical and mental health issues in the WFH group, which were associated with home-office work environments and contrasted with observations from a traditional workspace. Despite this body of work, many factors, for example, home office environment setting and specific organizational policy depending on work arrangement, remain to be considered to understand the future of managing the health of individuals who work from home. Thus, more research is needed to identify differences between the WFH and not-WFH groups, and the factors influencing health behaviors, physical and mental health, and organizational (work policy and shift) transition relationships in not-WFH groups.

Early-career workers are known to be vulnerable to safety and health risks at work.[29] A critical finding from our study was the necessity to manage mental distress in younger workers with <5 years' job duration, both in WFH and not-WFH groups. This was supported by previous studies, which showed that work-related stressors such as poor job control negatively impacted workers' mental health.[30,31] Individuals who work from home have also reported

TABLE 3 Regression results for effects of WFH on health outcomes (N = 12,438).

Health outcome	Variable	*b*	Linearized SE	*t*	95% CI Lower	95% CI Upper
Health behaviors						
Smoking[a]		0.18	0.07	2.72*	0.05	0.31
Alcohol consumption[a]		−0.32	0.06	−5.38**	−0.43	−0.20
Number of times fruit was eaten in the past month[b]	(constant)	33.65	0.69	48.99**	32.30	34.99
		2.74	1.18	2.32*	0.43	5.06
Number of times fruit is eaten per week[b]	(constant)	7.82	0.16	48.71**	7.50	8.13
		0.64	0.27	2.33*	0.10	1.18
Mental health[b,c]	(constant)	7.43	0.14	53.15**	7.16	7.71
		−1.56	0.18	−8.52**	−1.91	−1.20

Note: Reference group is WFH.

Abbreviations: CI, confidential interval; SE, standard error; WFH, working from home.

[a]Ordinal logistic regression was applied.

[b]Linear regression was applied.

[c]Sample size of 12,436.

*$p < 0.05$; **$p < 0.001$.

particular challenges related to performing unskilled work, technical issues with remote systems, inadequate social support, and communication at work.[32] To manage mental health, enrollment in employee assistance programs (EAPs) and other occupational e-mental health interventions at workplaces have been recommended.[33,34] However, research focused on young, early-career workers has been scarce. One longitudinal study of individual mental health coaching services provided by an EAP in the United States during the COVID-19 pandemic showed a significant reduction in the severity of depression and the percentage of employees at risk of developing clinical depression.[33] Based on our findings, we recommend regular evaluations of mental distress in young workers with shorter than 5 years' work experience and the establishment of a managing system. Occupational health professionals or human resources departments can point those with high distress to suitable resources. Providers and managers can thus build a rapport with employees and connect them to organizational resources such as EAPs.

4.1 | Strengths and limitations

This study has a few strengths. First, to the best of our knowledge, it is one of the first to compare health outcomes between workers in WFH and not-WFH groups using US state-level population survey data. Second, our statistical methods and findings can be harnessed to formulate hypotheses about the effects of WFH and not-WFH settings on workers' health. We minimized variance errors in the public data set by accounting for sample weighting, as recommended by CHIS. Based on our findings, we hypothesize directly that the health management of WFH employees should be prioritized over that of not-WFH employees. This can be tested using the CHIS confidential datasets. Third, our study explored the possibility of finding a potential key covariate for health outcomes. No study has reported on this data set and the relationship between health outcomes and occupation. Furthermore, all of the occupation and industry categories (>10 each) showed high variation in each sample. Thus, investigations of the relationship between specific occupations and health behaviors are needed in the future.

Our study findings are subject to a number of limitations. First, we faced a data limitation as we used public data. We could not minimize variance differences any further by applying strata as this could only be done for the confidential data set. Second, we could not explore some health behaviors. For example, variables related to physical health could not be obtained from the 2021 CHIS data set. A lack of variables related to physical activity in the 2021 data sets (both public and confidential) precluded analysis of physical activity. Third, the definition of WFH, a terminology used on the CHIS data dictionary,[10–14] was not entirely clear or inclusive. WFH is commonly conflated with telecommuting or remote work. The US Department of the Interior[35] has stated that "remote work is an arrangement under which an employee is not expected to report to an agency worksite on a regular and recurring basis—the remote work location is their official duty station." Telecommuting denotes the utilization of technology to replace the need for physical commuting to a work location.[36] Based on this definition, remote work or telecommuting can be considered WFH or working from another location excluding the workplace. Therefore, it was not clear whether our WFH category, based on the data dictionary or questionnaire, could be extended to include remote work.[10]

5 | CONCLUSION

Using state-level population data, this study found that the overall health outcomes (health behaviors and mental health) of individuals in WFH group were worse than the not-WFH group. This finding illuminates the need for periodic evaluation of health status and adequate health management for employees who work from home. In addition, the findings of this study also suggest that the early detection of mental health issues and provision of appropriate behavioral health intervention for young workers with high distress should be implemented at the organization level. This is particularly important because early career workers with less than 5 years' job duration reported more mental distress in both the WFH and not-WFH groups. This study highlighted the need to consider the mental well-being of young workers irrespective of work setting.

AUTHOR CONTRIBUTIONS

Sungwon Park, Chang Gi Park, and OiSaeng Hong conceptualized and designed the study together. Sungwon Park acquired data and performed the data analysis under the guidance of Chang Gi Park. Sungwon Park interpreted the results of the analysis, and Chang Gi Park and OiSaeng Hong verified the findings. Sungwon Park drafted the manuscript. Chang Gi Park and OiSaeng Hong contributed to reviewing the manuscript and editing the manuscript. Sungwon Park, Chang Gi Park, and OiSaeng Hong confirmed all the contents in the final version and agreed to the final approval of the version to be published.

ACKNOWLEDGMENTS

This study was supported by the first author's start-up research fund from the School of Nursing, University of Michigan.

CONFLICTS OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest.

DISCLOSURE BY AJIM EDITOR OF RECORD

John Meyer declares that he has no conflict of interest in the review and publication decision regarding this article.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in UCLA Center for Health Policy Research at https://healthpolicy.ucla.edu/chis/Pages/default.aspx.

ETHICS APPROVAL AND INFORMED CONSENT

The public data from California Health Interview Survey was analyzed after determination by the Institutional Review Board at University of Michigan, which determined that the data did not require approval for human subjects as the information was obtained from publicly available data sets (Protocol No. HUM00231930).

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How to cite this article: Park S, Park CG, Hong O. Exploring the characteristics and health outcomes of working from home: analysis of 2021 California Health Interview Survey data. *Am J Ind Med*. 2024;67:119-128. doi:10.1002/ajim.23556