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A secondary analysis of the role of geography in engagement and outcomes in a clinical trial of an efficacious Internet intervention for insomnia☆

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ABSTRACT

Background: Online interventions for insomnia can increase access to treatments for those with limited access to services. What remains unknown is whether individuals from more isolated (vs. more densely populated) regions engage with, and benefit as much from, an online intervention. This secondary analysis examined the relationship of geographical indices with engagement and outcomes of an efficacious, fully automated online cognitive behavioral therapy for insomnia (CBT−I) program (Sleep Healthy Using the Internet-SHUTi).
Method: 303 participants (M_{age} = 43.3; SD = 11.6) were randomly assigned to SHUTi or an online patient education condition and assessed at baseline and post intervention. Rural code of participants was determined using participant zip codes. Distance to the nearest sleep medicine provider was calculated as the distance between the center of the nearest provider's city (from a publicly available list of CBT-I providers) and the center of the participants' zip code. Adherence outcomes were number of intervention core completions, sleep diaries, and logins. Sleep outcomes were insomnia severity as well as sleep onset latency and wake after sleep onset derived from online sleep diaries.
Results: Individuals were from a range of geographic locations. Most lived in fairly densely populated areas; however, there was a large variation in distance to the nearest sleep medicine provider. Findings indicate that the efficacy, adherence, and engagement with SHUTi were not impacted by where people lived. Controlling for age and gender did not impact any of the relationships among geography variables (i.e., distance, ruralness) and adherence or sleep related outcomes.
Conclusions: Internet interventions must demonstrate that they can overcome obstacles posed by geography. This is the first study to examine the geographic location of participants and its association with engagement with, and outcomes of, online CBT-I.

1. Introduction

Where people live in the U.S. significantly predicts level of access to health services (Arcury et al., 2005). Not surprisingly, those who live in less densely populated areas have fewer options for specialty health care (Aboagye et al., 2014). The Internet, however, has the potential to reduce the geographical inequalities of care access by providing a vehicle to bring services and treatments to individuals regardless of where they live. A high rate of technology adoption in traditionally underserved areas has narrowed the digital divide. According to a recent national survey, 89% of American adults overall, and 78% of adults in rural areas, use the Internet (http://www.pewinternet.org/fact-sheet/internet-broadband/, 2018). Although Internet interventions have been shown to be highly effective at addressing a wide range of disorders (Christensen et al., 2004; Ritterband et al., 2017; Zachariae et al., 2018), there is limited understanding as to whether individuals from urban and rural areas differ in how they engage with, and ultimately benefit from, Internet interventions.

Behavioral treatment of insomnia is a practical use-case for examining the relationship of geography and engagement and outcomes.

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Behavioral sleep medicine providers, like most specialty healthcare professionals, tend to cluster in highly populated regions. This clustering results in limited access to in-person behaviorally-based insomnia treatment for individuals in more isolated regions. In fact, this is a major criticism of the treatment (Thomas et al., 2016). Making treatment available to individuals in rural areas is important, though, as studies have found that insomnia rates are just as high in more rural areas compared to other regions (Hartz et al., 2007). As a means of addressing this, online interventions for insomnia have been developed and demonstrate strong efficacy in improving sleep-related outcomes in individuals with insomnia (Ritterband et al., 2009, 2017; Zachariae et al., 2016).

To date, what has not been examined is how geographic diversity potentially influences engagement and outcomes; specifically, how isolated one is from a behavioral sleep medicine provider, has not yet been explored. Individuals that live farther from (vs. closer to) a behavioral sleep medicine provider may not benefit as much from Internet delivered CBT-I due to having relatively less contact with health care providers in general, leading to less familiarity with, and trust of, health care providers (Spleen et al., 2014) such as CBT-I specialists. Studies have shown that individuals in smaller and less populated areas may have concerns about stigma and the fear of family or community disapproval of receiving psychotherapy (Larson and Corrigan, 2010). These individuals are also more likely to endorse attitudes such as self-reliance and the belief that an illness will improve on its own without treatment (Steele et al., 2007). However, individuals who live farther away from a behavioral sleep medicine provider may benefit just as much from Internet delivered CBT−I, if not more, than those who live closer, given the lack of accessible health care options.

The purpose of this investigation is to examine the relationship of geographical indices (including rural code of participants, distance to nearest behavioral sleep medicine provider) with engagement and outcomes of an already proven efficacious online cognitive behavioral therapy for insomnia (CBT−I) program, Sleep Healthy Using the Internet (SHUTi) (Christensen et al., 2016; Ritterband et al., 2009, 2017). We characterize the geographic dispersion of the sample of insomnia participants who were enrolled in a large US trial of the efficacy of SHUTi, and examine whether where users live influenced their engagement with, and benefit from, the intervention.

2. Method

2.1. Study design and participants

Data and analyses were based on a randomized controlled trial in which participants were blinded to study arm assignment. Geographic and demographic variables were assessed at baseline, and sleep outcome variables were assessed at baseline, post intervention (i.e., 9 weeks after baseline), 6 months after the intervention period, and 12 months after the intervention period (Ritterband et al., 2017). Participants were recruited nationally (US) via online advertisements and online posts, including a local university clinical trial site, as well as posts to online sites, such as Facebook and Craigslist. The study was approved by the local Institutional Review Board.

Adults with regular Internet access were eligible to participate if they reported: 1) sleep-onset insomnia and/or sleep maintenance insomnia as defined by > 30 min for at least 3 nights/week for at least 6 months; 2) average total sleep time ≤ 6.5 h, and 3) sleep disturbance (or associated daytime symptoms) causing significant distress or impairment in social, occupational, or other areas of functioning. Exclusion criteria included: 1) presence of another untreated sleep disorder; 2) an irregular schedule which would prevent adoption of intervention strategies; 3) pregnancy; 4) current behavioral treatment for insomnia; and 5) initiation of psychological treatment in the previous three months. Individuals with severe depression (or with moderate/severe suicidality), bipolar disorder, and/or alcohol or other substance disorder in the previous year were excluded. Overall, the study sample consisted of 303 participants (72% female) between the ages of 21 and 65 (M_{age} = 43.3, SD = 11.6). Participants were 84% White, 7% Black, 4% Asian, and 5% "other." Overall, participants were well educated with 77.6% reporting at least a college degree. Participants were randomly assigned to SHUTi or a patient education condition. They completed online measures, including demographics and location, on the study interest form and pre-treatment questionnaires.

Severity of insomnia symptoms was assessed using the Insomnia Severity Index (ISI; Bastien et al., 2001), a 7-item measure with scores ranging from 0 to 28. Participants rated (0 = none to 4 = very severe) the degree to which they had insomnia signs and symptoms (e.g., difficulty falling asleep; extent sleep problems interfere with daily functioning). Higher scores are indicative of more severe insomnia severity. Internal consistencies of the ISI were α = 0.66 and 0.89 at baseline and post-assessment, respectively. The ISI has good sensitivity in detecting cases of insomnia and has been validated for online delivery (Thorndike et al., 2011).

Sleep diaries were collected online and provided data related to time in bed, length of sleep onset, number and duration of awakenings, perceived sleep quality, and rising time. Data was collected prospectively for 10 days (during a 2-week period) at each of the four assessment periods. Values for sleep onset latency (SOL) and wake after sleep onset (WASO) were averaged across the 10 days of diaries at each assessment period. Prospective sleep diaries are a well-validated method of assessing insomnia (Buysse et al., 2006).

Participants responded to questions about employment status ("Are you currently employed (working for pay)?"), healthcare insurance ("Do you have any kind of health care coverage, including health insurance, prepaid plans such as HMOs, or government plans such as Medicare?"), and whether previous treatment for insomnia had been sought. Participants also rated their comfort (1 = Neither comfortable nor uncomfortable; 5 = Very comfortable) with the Internet ("How comfortable are you in your use of the Internet?").

Rural-urban commuting area (RUCA) codes V2.0 from the United States Department of Agriculture were determined using participant zip codes. RUCA codes range from 1 (most metropolitan) to 10 (most rural) and are based on U.S. Census tract data of population density, urbanization, and daily commuting. RUCA codes have been extensively used as a reliable measure of urbanization in epidemiologic studies (Hall et al., 2006). In the current sample, 68% of participants resided in an area characterized as most urban/metropolitan (RUCA = 1), 30% resided in an area characterized as metropolitan/micropolitan (RUCA = 2–6), and 2% resided in an area characterized as small town/rural (RUCA = 7–10).

2.2. CBT-I providers

A list of 425 CBT-I providers, constructed for a previous publication (Thomas et al., 2016) examining the location of CBT-I providers, was used in this study. This list was first derived by identifying individuals certified in Behavioral Sleep Medicine as well as practitioners listed in the Society of Behavioral Sleep Medicine website (see Thomas et al., 2016). This list was then updated with providers' most recently-updated locations based on their profiles at the American Academy of Sleep Medicine and Sleep Research Society. To identify additional providers not affiliated with the above-listed groups, surveys were sent to e-mail listservs, including the Behavioral Sleep Medicine Group and the Behavioral Therapy for Insomnia Roster.

2.3. Conditions

2.3.1. Online CBT−I

Half the participants were randomized to receive SHUTi, a fully automated web-based program based on CBT−I, tailored to individual users, and designed according to the Model for Internet Interventions (Ritterband et al., 2009). SHUTi has been found to be more efficacious than online patient education in improving primary sleep outcomes (insomnia severity, sleep onset latency, wake after sleep onset), with the majority of SHUTi users achieving insomnia remission status one year later (Ritterband et al., 2017). SHUTi is based on foundational principles of in-person CBT—I, including sleep restriction, stimulus control, cognitive restructuring, sleep hygiene, and relapse prevention (see Thorndike et al., 2008 (Thorndike et al., 2008) for a detailed description of the SHUTi intervention).

Number of core completions and intervention logins served as metrics of engagement. Each core was coded dichotomously (0 = not completed, 1 = completed) for each SHUTi user. Number of core completions reflects the highest number of cores a user completed (0–6). Number of diary completions reflects the total number of sleep diary entries that a user completed during the intervention. Logins were derived from timestamps of each time a user signed into SHUTi during the intervention period that were at least 5 min apart.

2.3.2. Online patient education control

The online patient education program served as a sound control condition, providing accurate information regarding insomnia symptoms, causes and impact/prevalence of insomnia, as well as basic lifestyle and behavioral strategies to improve sleep. Content was based on reviews of insomnia-focused websites.

2.4. Data analysis

In order to quantify participants' access to a sleep specialist, the coordinates of the centroid of each participant's zip code in the U.S. and the coordinates of each CBT-I provider's city in the U.S. were determined using PROC GEOCODE in SAS. The distance between each participant and the nearest CBT-I provider was calculated in two ways. First, the straight-line distance was obtained using the GEODIST function in SAS. The result is calculated in miles and represents the direct geographical distance between the center of each participant's zip code and the center of the city of the nearest CBT-I provider, and therefore is an underestimate of the actual distance someone must travel between these two points by road. Second, we used SAS code to query Google Maps for the shortest *driving* distance, in miles, between the patient and the nearest CBT-I provider. The locations of each participant's zip code and each CBT-I provider's city were displayed graphically using PROC GMAP (Fig. 1). Table 1 contains descriptive statistics of the SHUTi and online patient education groups. Analyses focused on those within the SHUTi condition. SOL and WASO were log-transformed before analysis to reduce skew. Residual scores of ISI, SOL, and WASO at post (i.e., scores at post-intervention from which baseline scores were partialed out) were computed to account for baseline levels. A series of linear regression analyses were computed. Separate analyses were conducted for the dimensional predictors rural code and distance to the nearest sleep medicine provider. Residual scores of ISI, SOL, and WASO served as separate outcome variables. These analyses were done in SPSS 24.0.

For those within the SHUTi condition, linear regression analyses were also computed to examine whether rural code and distance to the nearest sleep medicine provider (as continuous predictors) was associated with the SHUTi adherence metrics (number of core completions, sleep diaries, and logins).

For each of the linear regression analyses described above, a sensitivity analysis was performed to examine the robustness of findings after controlling for demographic variables. Hierarchical linear regression analyses were conducted in which distance/rural code was entered in the first step, age was entered in the second step, and gender was entered in the third step, to determine whether controlling for age and gender impacted the relationship between geography variables (i.e., distance and ruralness) and adherence or sleep related outcomes.

3. Results

Primary outcomes and cognitive mechanisms of sleep outcomes from this study have been previously published (Chow et al., 2018; Ritterband et al., 2017). Table 2 contains frequency counts of the types of prior insomnia treatments individuals sought by participants, as well as demographic variables and *p*-values of contrasts (from χ^2 tests) between those in the current sample that: a) live more vs. < 25 miles/40 km in straight-line distance from the nearest behavioral sleep provider; and b) do vs. do not live in the most metropolitan areas. Consistent with prior findings (Aboagye et al., 2014), those in the current sample that: a) live more (vs. less) than 25 miles/40 km in straight-line distance from the nearest behavioral sleep provider, reported lower rates of visiting a sleep clinic and a sleep specialist for their sleep problems, and reported less comfort with using the Internet.

Fig. 1 presents a visualization of the number of CBT-I providers in the U.S., and the driving distance between SHUTi participants and CBT-I providers. The average straight-line distance to the nearest sleep provider across conditions was 24.66 miles/39.69 km, with a standard deviation of 41.68 miles/67.08 km and range between 0.15 and 254.89 miles (0.24 and 410.21 km). The average driving distance to the nearest sleep provider across conditions was 31.94 miles/51.40 km, with a standard deviation of 54.15 miles/87.15 km and range between 0.40 and 423 miles (0.64 and 680.75 km). Table 3 contains descriptive statistics for primary sleep outcomes and adherence metrics by straight-line distance to nearest behavioral medicine sleep provider and rural-urban commuting area code.

Linear regression analyses revealed that straight-line distance to the nearest sleep medicine provider did not significantly predict post-intervention Insomnia Severity (β = -0.05, p = .57), SOL (β = 0.02, p = .84), or WASO (β = 0.004, p = .97). Similarly, driving distance to the nearest sleep medicine provider did not significantly predict post-intervention Insomnia Severity (β = -0.05, p = .57), SOL (β= 0.01, p = .89), or WASO (β = 0.01, p = .93). There were also no significant associations between RUCA code and Insomnia Severity (ß = -0.10, p = .26), SOL (ß = 0.11, p = .23), or WASO (β = -0.03, p = .76).[1]

On average, individuals completed 4.68 (*SD* = 1.93) cores, completed 39.88 sleep diaries (*SD* = 18.74), and logged in to the program 28.0 (*SD* = 21.79) times. Regression analyses indicated that straight-line distance to the nearest sleep medicine provider was not significantly associated with number of core completions (ß = -0.008, p = .920), number of sleep diaries completed (ß = -0.03, p = .72), or logins (ß = -0.07, p = .39). Similarly, driving distance to the nearest sleep medicine provider was not significantly associated with number of core completions (β = -0.02, p = .82), number of sleep diaries completed (β = -0.02, p = .79), or logins (β = -0.02, p = .83). There were also no significant associations between RUCA code and number of core completions (β = 0.04, p = .66), number of sleep diaries completed (β = 0.002, p = .99), or logins (β = -0.03, p = .77).

3.1. Robustness of findings

For those in the SHUTi condition, controlling for age and gender did not significantly impact the relationship between straight-line distance to the nearest sleep medicine provider and: a) post-intervention Insomnia Severity (β = -0.05, p = .57 after controlling for age; β = -0.04, p = .45 after controlling for age/gender); b) post-intervention SOL (β = 0.02, p = .85 after controlling for age; β = 0.03, p = .74 after controlling for age/gender); and c) post-intervention WASO (β = 0.003, p = .97 after controlling for age; β = 0.01, p = .92 after controlling for age/gender). Similarly, controlling for age and gender did not significantly impact the relationship between driving distance

[1] Similar results were obtained when rural code was coded as a dichotomous variable (1 = rural code of 1, 0 = rural code > 1).

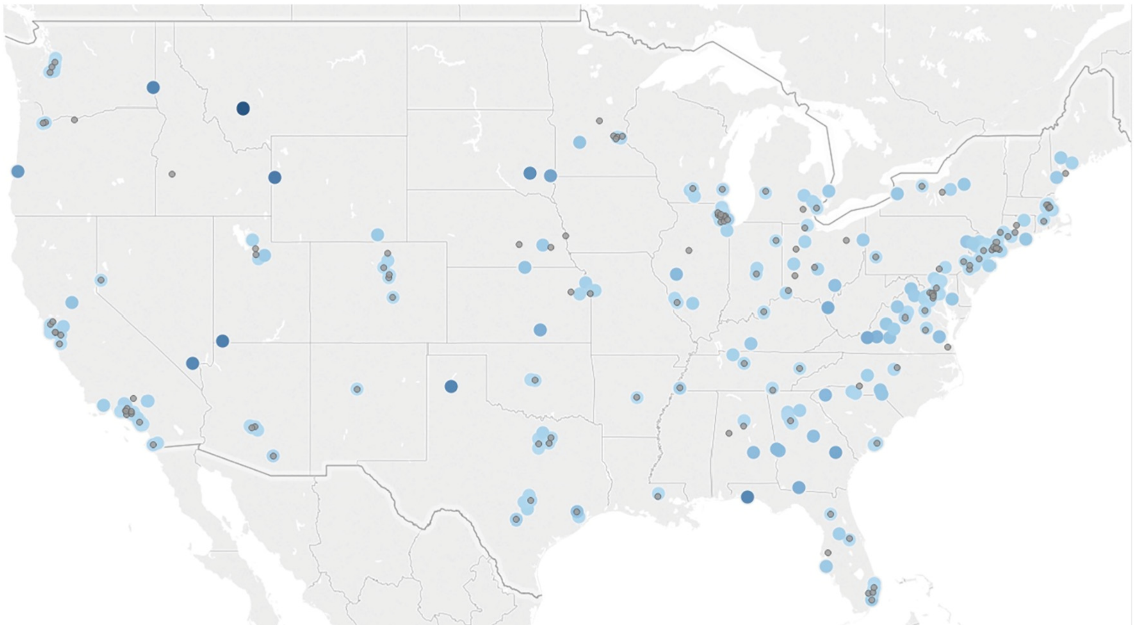

Fig. 1. Locations of behavioral sleep medicine providers (small grey dots) study participants (larger blue dots, with darker shades indicating longer distances to a sleep medicine provider) and in the U.S. (For interpretation of the references to color in this figure legend, the reader is referred to the online version of this chapter.)

Table 1
Descriptive statistics of SHUTi and Patient Education groups.

	SHUTi (n = 151)	Patient Education (n = 152)
Race	128 White 9 Black 7 Asian 7 Other	126 White 12 Black 5 Asian 9 Other
Hispanic (No.)	12	12
Education (years)	17.4 (2.8)	17.0 (2.8)
Age	43.8 (11.3)	42.8 (11.9)
Currently employed	Yes = 131 No = 20	Yes = 134 No = 18
Comfort with internet	Very comfortable = 135 Less than very comfortable = 16	Very comfortable = 133 Less than very comfortable = 19
Healthcare coverage	Yes = 130 No = 19 Don't know = 2	Yes = 131 No = 19 Don't know = 2
Rural Code	1 = 99 > 1 = 52	1 = 109 > 1 = 43
Distance to nearest sleep provider in miles	22.56 (37.83)	26.74 (42.21)

to the nearest sleep medicine provider and: a) post-intervention Insomnia Severity (β = -0.05, p = .56 after controlling for age; β = -0.04, p = .65 after controlling for age/gender); b) post-intervention SOL (β = 0.01, p = .89 after controlling for age; β = 0.03, p = .77 after controlling for age/gender); and c) post-intervention WASO (β = 0.01, p = .92 after controlling for age; β = 0.02, p = .86 after controlling for age/gender). Finally, controlling for age and gender did not significantly impact the relationship between RUCA code and: a) post-intervention Insomnia Severity (β= -0.10, p = .27 after controlling for age; β = -0.09, p = .30 after controlling for age/gender); b) post-intervention SOL (β = 0.11, p = .23 after controlling for age; β = 0.11, p = .20 after controlling for age/gender); and c) post-intervention WASO (β = -0.03, p = .73 after controlling for age; β = -0.03, p = .76 after controlling for age/gender).

In terms of SHUTi adherence metrics, controlling for age and gender did not significantly impact the relationship between straight-line distance to the nearest sleep provider and: a) number of core completions (β = -0.01, p = .93 after controlling for age; β = -0.02, p = .86 after controlling for age/gender); b) number of sleep diaries completed (β = -0.03, p = .73 after controlling for age; β = -0.04, p = .64 after controlling for age/gender); and c) logins (β = -0.02, p = .77 after controlling for age; β = -0.03, p = .69 after controlling for age/gender). Similarly, controlling for age and gender did not significantly impact the relationship between driving distance to the nearest sleep provider and: a) number of core completions (β = -0.02, p = .82 after controlling for age; β = -0.03, p = .76 after controlling for age/gender); b) number of sleep diaries completed (β = -0.02, p = .77 after controlling for age; β = -0.03, p = .68 after controlling for age/gender); and c) logins (β = -0.02, p = .80 after controlling for age; β = -0.03, p = .73 after controlling for age/gender). Finally, controlling for age and gender did not significantly impact the relationship between RUCA code and: a) number of core completions (β = 0.04, p = .65 after controlling for age; β = 0.04, p = .66 after controlling for age/gender); b) number of sleep diaries completed (β = -0.02, p = .84 after controlling for age; β = -0.02, p = .82 after controlling for age/gender); and c) logins (β = 0.02, p = .83 after controlling for age; β = 0.02, p = .85 after controlling for age/gender).

4. Discussion

In this secondary analysis of data from a large, randomized national trial of an effective online intervention for insomnia, findings suggest that participants' engagement and benefit from the intervention did not differ based on geographical indices. Insomnia participants in the current study lived in a range of geographic locations. While most lived in fairly densely populated areas, there was a large variation in distance to the nearest sleep medicine provider for participants. However, findings indicate that the engagement with and efficacy of SHUTi was not impacted by geography, providing novel evidence to support online interventions as an effective means to disseminate care to traditionally underserved individuals regardless of locality.

The average straight-line distance to the nearest sleep provider was 25 miles/40 km, with the greatest distance being over 250 miles/402 km. The actual driving distance was even farther, with the average driving distance to the nearest sleep provider across conditions being

Table 2
Type of prior insomnia treatment sought before participating in study, demographic variables, and χ2 test of significance for each variable.

	Straight-line distance to nearest sleep provider		p	Rural-Urban Commuting Area Code (RUCA)		p
	≤25 miles or 40 km (n = 220)	> 25 miles or 40 km (n = 73)		RUCA = 1 (n = 203)	RUCA > 1 (90)	
		Prior insomnia treatment				
Family doctor	108 (49%)	39 (53%)	0.52	100 (51%)	47 (52%)	0.64
Sleep clinic	46 (21%)	7 (10%)	0.03	40 (20%)	13 (14%)	0.28
Sleep specialist	52 (24%)	5 (7%)	0.002	43 (21%)	14 (16%)	0.26
Mental health professional	43 (20%)	12 (16%)	0.56	40 (20%)	15 (17%)	0.54
Sleep medication	111 (51%)	44 (60%)	0.15	102 (50%)	53 (59%)	0.17
Self-help book	42 (19%)	7 (10%)	0.06	39 (19%)	10 (11%)	0.09
Internet information	143 (65%)	51 (70%)	0.45	130 (64%)	64 (71%)	0.24
		Demographic variables				
White/Race (% White)	178 (81%)	66 (90%)	0.06	159 (78%)	85 (94%)	0.001
Education	17.1 (3.1)	17.4 (3.1)	0.51	17.0 (2.7)	17.7 (3.0)	0.06
Age	42.6 (11.4)	44.2 (11.5)	0.29	42.5 (11.2)	44.0 (12.0)	0.31
Is currently employed	179 (81%)	56 (77%)	0.39	162 (80%)	73 (81%)	0.80
Has comfort w/internet	200 (91%)	58 (80%)	0.02	178 (88%)	80 (89%)	0.59
Has healthcare coverage	191 (87%)	62 (85%)	0.67	179 (88%)	74 (82%)	0.13

Note. 10 participants did not provide a validated zip code.

Table 3
Descriptive statistics (mean, SD) for primary sleep outcomes and adherence metrics, based on distance to nearest behavioral medicine sleep provider and rural-urban commuting area code.

	Distance to nearest behavioral sleep provider		Rural-Urban Commuting Area Code (RUCA)	
	≤25 miles or 40 km	> 25 miles or 40 km	RUCA = 1	RUCA > 1
ISI Baseline	16.77 (3.67)	17.56 (4.49)	17.01 (4.09)	17.06 (3.89)
ISI Post	9.32 (5.46)	9.43 (5.64)	9.52 (5.82)	8.95 (4.76)
SOL Baseline	43.29 (33.13)	42.04 (25.73)	44.37 (32.52)	40.30 (29.44)
SOL Post	24.19 (30.53)	22.81 (14.40)	24.18 (31.63)	23.20 (16.32)
WASO Baseline	85.27 (54.88)	69.81 (32.75)	85.99 (54.17)	73.11 (43.03)
WASO Post	39.73 (34.03)	38.19 (33.85)	39.85 (35.55)	38.36 (30.40)
No. Core Completions	4.65 (1.91)	4.76 (1.92)	4.71 (1.96)	4.63 (1.89)
Sleep Diaries	38.45 (19.03)	41.18 (17.86)	38.99 (19.38)	38.67 (17.63)
Logins	27.88 (23.00)	28.94 (18.74)	28.67 (22.79)	26.73 (19.90)

Note. ISI = Insomnia severity index; SOL = Sleep onset latency; WASO = Wake after sleep onset; No. Core Completions = Number of core completions. SOL and WASO values were log-transformed before conducting analyses.

32 miles/51 km, with the greatest distance being over 420 miles/676 km. This suggests that an online insomnia intervention can meet the need for those with limited or no options for in-person treatment. Importantly, the current findings suggest that relative geographic isolation did not influence the amount of program utilization. Regardless of where participants lived, most reported seeking some type of prior treatment for their insomnia, although those in relatively isolated areas had a high rate of seeking treatment from a family doctor, searching for insomnia information on the Internet, and taking medications for their insomnia. In-person models of treatment delivery may not be feasible or sustainable for individuals who need to travel great distances or who lack convenient access to transportation. Further, while the vast majority of sleep specialists reside in densely populated regions, there is an overflow of demand for their services (Flemons et al., 2004; Thomas et al., 2016; Watson et al., 2017). Thus, an online insomnia intervention may also be a viable option for those who live in relatively densely populated areas but are unable to see a sleep specialist. Thus, while the current study found that geographic variables did not influence the amount people benefitted from SHUTi, future work should continue to examine whether digital interventions are equally beneficial for users in different regions.

4.1. Limitations and future directions

There were some limitations of the present investigation. Participants were predominantly White, well educated, working, and had a high level of comfort with the Internet, perhaps reflecting an artifact of how people were recruited into the study. Future studies should therefore examine health disparity variables (e.g., race, income) in a larger, more diverse sample. While the analyses conducted in this investigation found no evidence that the impact of SHUTi was affected by where users lived, replication of these results in a larger sample, with more individuals in highly rural areas, would help increase confidence in these findings, to determine whether those who live in rural versus urban areas benefit equally. Specifically, because participants in the current investigation responded to study ads, it is possible that self-selection bias obscured differences that do exist due to geography. In the current sample, there was a trend for individuals in more metropolitan areas to be more likely to report using bibliotherapy versus those in more rural areas. The potential for selection bias also has implications of how digital health interventions are disseminated. For example, researchers that advertise a digital health intervention to the general population may end up with strong results that are not generalizable to those in rural areas.

The current investigation focused on the distance between participants and their nearest CBT-I provider. Although we were limited to using CBT-I providers' cities because this was the most precise location data available in the publicly available list, future studies may wish to obtain more precise location data for participants. However, many factors, such as transportation options (e.g., private car, public bus), traffic patterns, income, and scheduling, may influence one's ability to visit a CBT-I specialist. Although controlling for age and gender did not impact any of the relationships among geography variables (i.e., distance and ruralness) and adherence and sleep related outcomes, researchers should continue to examine other variables that may impact this relationship. There may be less variation in ruralness due to the large number of participants that lived in a highly metropolitan area. Future studies may wish to stratify their samples based on rurality, in order to better understand the impact of geography on health outcomes.

5. Conclusion

Insomnia is a large public health burden that cannot be fully or solely addressed using in-person treatment models. Further, many who suffer from insomnia do not have convenient access to in-person treatment. Thus, an important step to fulfilling the promise of Internet interventions is to clearly demonstrate that they can overcome obstacles posed by geography. Findings from the present investigation suggest that where people live does not impact how much they engage or benefit from an online insomnia intervention.

Declaration of competing interest

Dr. Ritterband has equity ownership in BeHealth Solutions, LLC, a company that has licensed software from the University of Virginia. Dr. Ritterband is also a consultant to two companies focused on the commercialization of digital therapeutics: Pear Therapeutics, who have licensed the SHUTi program from the University of Virginia, and Mahana Therapeutics. These companies had no role in preparing this manuscript. The terms of these arrangements have been reviewed and approved by the University of Virginia in accordance with its policies. Frances P. Thorndike has equity ownership in BeHealth Solutions, LLC, a company that has licensed software from the University of Virginia, and is employed by Pear Therapeutics, who have licensed the SHUTi program from the University of Virginia.

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