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Information Seeking Behavior and Mental Health Service Utilization: Using Big Data Tools to Examine Temporal Trends and Geographic Variations in ADHD

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INFORMATION SEEKING BEHAVIOR AND MENTAL HEALTH SERVICE UTILIZATION: USING BIG DATA TOOLS TO EXAMINE TEMPORAL TRENDS AND GEOGRAPHIC VARIATIONS IN ADHD

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To: Dean Michael Heithaus
College of Arts, Sciences and Education

This dissertation, written by Xin Zhao, and entitled Information Seeking Behavior and Mental Health Service Utilization: Using Big Data Tools to Examine Temporal Trends and Geographic Variations in ADHD, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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Date of Defense: May 24, 2021.

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Vic President for Research and Economic Development
and Dean of the University Graduate School

Florida International University, 2022

DEDICATION

I dedicate this work to my beloved parents, grandparents, and brother, who have unconditionally loved me and supported me.

献给我的爸爸妈妈，姥姥姥爷和弟弟：感谢他们无条件的爱，支持，与鼓励。家在远方，路在脚下；有了他们，才有我追求梦想的勇气和恒心。希望我的家人永远健康快乐。希望姥爷在另一个没有病痛的世界里平安喜乐。

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ABSTRACT OF THE DISSERTATION

INFORMATION SEEKING BEHAVIOR AND MENTAL HEALTH SERVICE UTILIZATION: USING BIG DATA TOOLS TO EXAMINE TEMPORAL TRENDS AND GEOGRAPHIC VARIATIONS IN ADHD

by

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Professor Stacy L. Frazier, Major Professor

Persistently low rates of children's mental health service utilization have inspired close examination of barriers to care that point to sociodemographic and geographic disparities. Information science points to socioeconomic disparities in health information seeking (access and need) that may decrease corresponding to increasing rates of online searching in underserved communities. Three specific aims were examined: Aim 1. Examine changes in information seeking over time; Aim 2. Examine geographical variations of online searches; Aim 3. Examine the connection between state-level information-seeking variations and individual diagnoses.

The dissertation uses publicly available data and big data methods (i.e., time series analyses, machine learning approaches, multilevel modeling) to examine and improve the speed and reach of scientific communication. Time series analyses revealed that 1) queries of "ADHD medication" increase, while queries for "ADHD therapy" remain relatively low despite a positive linear trend, 2) breaks coincided with a decrease in search interest, while post-break periods illustrated a rise, and the ADHD Awareness

Month (October) coincided with a rise of public interest in all four search terms. Machine learning algorithms suggested that seeking ADHD-related information online was relatively more important in states with a higher percentage of underserved families (e.g., Hispanic/Latinx youth) and/or with more families who are already connected to systems of care. Multilevel modeling analyses revealed that racial/ethnic disparities in ADHD diagnoses remain and state-level search interest positively predicted ADHD diagnoses after controlling for sociodemographic variables.

The anonymous and accessible nature of seeking information online makes search engines like Google important sources of mental health information, especially among underserved and marginalized groups. Findings suggest need for future research and highlight internet-based opportunities for understanding and detecting inequalities in need for and access to empirically supported information and care.

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I. INTRODUCTION TO THE RESEARCH

I am building a program of research to understand connections between online health information-seeking behaviors and mental health service utilization. I have prioritized three areas of training: 1. Advanced analytic tools, 2. Attention deficit hyperactivity disorder (ADHD), and 3. Dissemination science. I have learned (through coursework, a quantitative minor, and as a Teaching Assistant) and applied multilevel modeling and machine learning techniques. I have contributed to the understanding of economic impact (Zhao et al., 2019), functional assessment (Zhao et al., under review), and interventions of ADHD (Schatz et al., 2020). Findings motivated me to begin examining mental health inequities and barriers to care. As my interest grew further in dissemination and implementation science, I designed my dissertation project with particular focus on mental health equity for marginalized families and public health models of care. I utilized publicly available data and big data methods to examine and improve the speed and reach of scientific communication.

Rationale for Research

Despite advances in evidence-based practice (Ng & Weisz, 2016), the prevalence and costs of untreated emotional and behavioral disorders, such as ADHD, among youth remains high (Doshi et al., 2012; Merikangas et al., 2011). Persistent disparities in mental health service need and utilization (Merikangas et al., 2011) may reflect sociodemographic differences in *health information seeking* (Zimmerman & Shaw, 2020), though few studies have examined the extent to which adequate and equitable information about mental health inspires treatment seeking among families. Findings from my dissertation project reveal temporal fluctuations and geographic variations in online mental health information-seeking patterns. My dissertation project (1) initiates a research agenda to improve the speed and reach of scientific communication and (2) provides a roadmap for leveraging internet search patterns to disseminate evidence-based information and educate consumers about mental health science and service across levels of care and stages of help seeking.

Presentation of Research Findings

My dissertation project explores aims to inform internet-based opportunities for dissemination and implementation. The research is described in three separate manuscripts. Paper 1 (Chapter 2) has been submitted to *Administration and Policy in Mental Health and Mental Health Services Research*. Chapter 2 presents temporal changes in information-seeking patterns related to ADHD (i.e., Google Trends Relative Search Volumes [RSVs] for “ADHD,” “ADHD treatment,” “ADHD medication,” “ADHD therapy”). Paper 2 (Chapter 3) has been submitted to *Journal of Attention Disorders*. Chapter 3 describes state-level variations in Google Trends RSVs and the relatively important variables to explain them. Machine learning algorithms suggested that seeking ADHD-related information online was relatively more important in states with a higher percentage of underserved families and/or with more families who are already connected to systems of care (e.g., youth with ADHD diagnoses or treatment) than other states. Paper 3 (Chapter 4) is intended for *Clinical Psychological Science* in the Special Issue on Understanding Ethnoracial Disparities and Advancing Mental Health Equity through Clinical Psychological Science. Chapter 4 described the relations among individual-level sociodemographic variables, state-level information-seeking patterns, and child’s current ADHD diagnoses. Multilevel modeling results suggested 1) individual-level racial/ethnic background and state-level information-seeking patterns predicted ADHD diagnoses; 2) the cross-level interaction of the two was not predictive for ADHD diagnoses. Future research directions have been discussed in Chapter 5.

II. MENTAL HEALTH INFORMATION-SEEKING ONLINE: A GOOGLE TRENDS ANALYSIS OF ADHD

This manuscript has been submitted to Administration and Policy in Mental Health, and thus adheres to its use of APA 7th Edition formatting guidelines.

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Abstract

Purpose. Health information influences consumer decision making to seek, select, and utilize services. Online searching for mental health information is increasingly common, especially by adolescents and parents. Informed by help-seeking models, we aim to examine historical trends and factors that may influence population-level patterns in information-seeking of attention deficit hyperactivity disorder (ADHD). *Methods*. We extracted Google Trends data from January 2004 to February 2020. Keywords included "ADHD," "ADHD treatment," "ADHD medication," and "ADHD therapy." We examined trends (systematic change over time) and seasonality (repeating pattern of change) via time-series analyses and graphics. We also used interrupted time-series analyses to examine the impact of celebrity and pharmaceutical events. *Results.* Queries of "ADHD medication" increase, while queries for "ADHD therapy" remain relatively low despite a positive linear trend. Searches for "ADHD treatment" displayed a downward trend in more recent years. Analyses on seasonality revealed that holiday breaks coincided with a decrease in search interest, while post-break periods illustrated a rise, and the ADHD Awareness Month (October) coincided with a rise of public interest in all four search terms. Celebrity effects were more prominent in earlier years; the "Own It" pharmaceutical campaign may have increased ADHD awareness and the specificity of searches for "ADHD medication." *Conclusions.* The anonymous, accessible, and low-cost nature of seeking information online makes search engines like Google important sources of mental health information. Changing search patterns in response to seasonal, advocacy, and media events highlight particular internet-based opportunities for raising awareness and disseminating empirically supported information.

Literature Review

Despite significant advances in evidence-based practice, including personalized therapy (Ng & Weisz, 2016), telehealth formats (Comer & Myers, 2016), and brief interventions (Schleider et al., 2020) for mental health problems, approximately one-half of adolescents do not receive treatment for clinically elevated symptoms (Merikangas et al., 2011). Of recent interest toward unpacking these disparities is a closer examination of the vast amount of information and resources available online, which may explain emergent associations between information- and help-seeking. For instance, a recent study of browsing histories (Schueller et al., 2020) shows that keywords entered in search engines are associated with perceived barriers to psychosocial treatment. It follows that search engine data related to mental health may reveal untapped opportunities to influence information- and help-seeking. In this paper, we used Google Trends (Google Inc., 2020) to explore information-seeking patterns related to Attention Deficit Hyperactivity Disorder (ADHD), a common, impairing, and widely searched neurodevelopmental disorder (Barkley, 2018; Danielson et al., 2018; Sage et al., 2018).

Help- and Information-Seeking

Three key processes have informed the development and revision of help-seeking models pertinent to youth mental health (Andersen & Newman, 2005; Eiraldi et al., 2006). First came Andersen and Newman's (1973) behavioral model of health service use in the medical field, highlighting societal and individual determinants of service utilization. Goldsmith, Jackson, and Hough (1988) proposed including cost-benefit analyses (i.e., assessing whether the benefits of seeking help justify the costs and efforts). Later, incorporating work based on Bronfenbrenner's (1979) ecological systems theory, researchers emphasized the importance of social networks and cultures in help-seeking models (Cauce et al., 2002; Srebnik et al., 1996). More recently, Eiraldi and colleagues (2006) examined facilitators and barriers across four linear stages of help-seeking – problem recognition, decision to seek help, service selection, and service use – and conceptualized that perceived severity and impairment of mental health problems motivated referrals (Parcesepe & Cabassa, 2013; Reardon et al., 2017). Help-seeking decisions may be voluntary or coercive (e.g., children may be required to initiate treatment prior to returning to school; Cauce et al., 2002). In either case, once the decision has been made to seek help, caregivers and patients rely on a cost-benefit analysis (Goldsmith et al., 1988) to compare available and accessible options (e.g., service costs and insurance concerns are common barriers reported by parents in US community samples; Reardon et al., 2017). Ultimately, the impact of services on reducing severity and impairment of mental health problems depends on the quality of treatment received *and* caregiver and patient adherence to treatment recommendations.

Central to help-seeking is information-seeking. Health information-seeking is broadly conceptualized as "the active pursuit of health information" (Zimmerman & Shaw, 2020, p. 5). Based on a range of theoretical frameworks across fields (Marton & Choo, 2012; Zimmerman & Shaw, 2020), health information-seeking can be understood as a function of *need* (interest, desire and perceived necessity of unknown health information) and *access* (availability, quality, and convenience of information sources). Symptom elevation and/or functional impairment among selves, relatives and friends (problem recognition) increase information needs and inspire health information-seeking (Mishra et al., 2009; Srebnik et al., 1996). Access to health information is fluid as it varies over time, corresponding to individual traits (e.g., knowledge, perceived stigma, and beliefs) and contextual factors (e.g., social network and cultures) to influence decision making to seek, select, and utilize services (Lannin et al., 2016; Mishra et al., 2009; Turner et al., 2015; Yigzaw et al., 2020).

Sources of health information include the internet, traditional media (e.g., library, books, brochures, magazines), social networks (e.g., family, peers, coworkers), and healthcare professionals(Cline, 2001; Gray et al., 2005). Compared to other sources, the internet is accessible (low cost), convenient (i.e., speed, ease), anonymous, private, and interactive(Cline, 2001; Jacobs et al., 2017; Kauer et al., 2014). As access to digital devices has increased in the past two decades (Pew Research Center, 2019), internet use also increased, while use of traditional media decreased (Jacobs et al., 2017). Although the internet does not replace health professionals as a health information source (Gray et al., 2005; Jacobs et al., 2017), many rely on search engines like Google as a first step (Lee et al., 2014). The internet is an especially important source for health information among individuals who have difficulty accessing timely services (Chen & Zhu, 2016) and those involved in youth-serving settings, such as adolescents(Gray et al., 2005), young adults (Kauer et al., 2014) and parents (Khoo et al., 2008; Kubb & Foran, 2020).

Health information, when pursued and consumed, can alter patients' preferences, decisions, and behaviors. Seeking health information online is associated with preferences for patient-centered (open, collaborative, and equal) care (Baldwin et al., 2008). Also, adults who used web search engines were more likely to decide to visit a health professional (help-seeking *decision*) as well as actually visit a physician (help-seeking *behavior*), compared to those who had not used search engines in a cross-sectional survey (Yigzaw et al., 2020). Notably, Yigzaw et al., 2020 reported *association* rather than *causal inference* (which requires temporal precedence), for online information-seeking and help-seeking in a cross-sectional survey; such associations are often moderated by factors such as age, symptom severity. It is worth noting that these findings reflect studies of “active searches for” rather than “passive receipt of” health information. For instance, simply receiving disorder-specific information (i.e., a short series of depression e-cards) did not yield positive changes, relative to a comparison condition, in beliefs of treatment efficacy, intention, or behavior to seek professional help (Costin et al., 2009).

Google Trends

Search engine data can be particularly useful in understanding mental health information-seeking patterns. Google holds a dominant market share (88%) in the United States (Statcounter, 2020) and represents a common source for health information-seeking (Lee et al., 2014). Google Trends is a viable tool to understand, monitor, and even forecast trends of information-seeking and public interest (Jun et al., 2018; Mavragani et al., 2018; Nuti et al., 2014). An increasing number of studies (20-fold from 2009 to 2018 on PubMed) have been using Google Trends data to examine causal inferences, temporal patterns, and/or geographical variations pertaining to various health conditions, including influenza, cancer, and mental health (Arora et al., 2019; Nuti et al., 2014). Examples related to mental health include understanding seasonal trends for information-seeking related to mood and neurodevelopmental disorders (Ayers et al., 2013; DeVilbiss & Lee, 2014) and the impact of celebrity events on suicide-related searches (Arendt & Scherr, 2017; Fond et al., 2015; Gunn III et al., 2020; Koburger et al., 2015).

ADHD, Information-Seeking, and Help-Seeking

ADHD is a burdensome, stigmatized, and untreated condition for millions of youth and adults (Barkley, 2018; Doshi et al., 2012; Fulton et al., 2015). ADHD incurs substantial economic burden to families and society in general (Doshi et al., 2012; Hinshaw & Scheffler, 2014; Zhao et al., 2019). Families of youths with ADHD are widely stigmatized (Hinshaw & Scheffler, 2014), as children with ADHD are perceived as more dangerous, lazier, and more shameful than children with asthma (see Parcesepe & Cabasssa, 2013, for a review). One in ten youths is diagnosed with ADHD; most are treated with psychotropic medications and one-quarter remain untreated (Coker et al., 2016; Danielson et al., 2018). Despite robust support for psychosocial interventions (Fabiano & Pyle, 2019; Schatz et al., 2020), fewer than half of insured children diagnosed with ADHD have received behavioral therapy for ADHD (Waxmonsky et al., 2019), highlighting the large science-to-service gap.

Online information may have the potential to bridge the gap, making it an excellent case to apply Eiraldi et al.'s (2006) aforementioned four-stage help-seeking model (from problem recognition to service use). Information needs are both general – knowledge about ADHD – and specific – knowledge about ADHD treatment (Ahmed et al., 2014; Akram et al., 2009; Rosenblum & Yom-Tov, 2017; Sciberras et al., 2010; Yu et al., 2019). Among a variety of search terms related to ADHD, Rosenblum and Yom-Tov (2017) reported "ADHD medication" as the most common search query after "ADHD" in Microsoft Bing search engine data. Beyond pharmaceutical treatment, information about psychosocial strategies is also commonly sought, especially among parents of children with suspected or confirmed ADHD diagnoses (Ahmed et al., 2014; Yu et al., 2019). Caregivers reported lacking ADHD-related knowledge, especially prior to their children's diagnoses (Ahmed et al., 2014); this was especially so for caregivers from racial/ethnic minority backgrounds (Bussing et al., 2007), highlighting that disparities in service utilization may, to some extent, reflect disparities in information access and help-seeking.

Information-seeking can impact the pathways from problem recognition to service utilization, as parents and teachers play vital roles in help-seeking of ethnic minority children with ADHD (Eiraldi et al., 2006; Gerdes et al., 2014; Haack et al., 2018). Across several survey studies, more than half of adolescents and parents identified the internet as their preferred information source when they want to learn about ADHD and its treatment (Bussing et al., 2012; Sciberras et al., 2010; Yu et al., 2019). In another survey study from Scotland, more than 80% of teachers chose the internet as their information source about ADHD and its pharmacological treatment (Akram et al., 2009). Rosenblum and Yom-Tov (2017) analyzed questions asked on Yahoo answers and demonstrated that parents suspected their children's ADHD as early as age two (problem recognition) and were more likely to seek ADHD-related information online (information-seeking) before their children were diagnosed (usually the first step of interfacing with services). Although most existing studies provide information related to the preferences, content, and pathways of information-seeking at the individual level (Akram et al., 2009; Bussing et al., 2012; Cunningham et al., 2009; Sage et al., 2018; Yu et al., 2019), these small-*N*, geographically restricted, and cross-sectional survey studies are often not theory-driven and offer limited insights into population-level patterns.

Trends, Seasonality, and Media Influence

Trends.

Trends in ADHD information-seeking. Over the past two decades, there appears to be an upward trend in reporting the internet as a preferred source for ADHD-related information in survey studies (Bussing et al., 2007, 2012; Sage et al., 2018). For instance, in a longitudinal study of a representative school district sample in Florida, 5% at the initial screening in 1998 (Bussing et al., 2007) and around 50% of the parents at the final follow-up in 2008 reported the internet as their preferred source for information about ADHD (Bussing et al., 2012). More recently, in a sample recruited in pediatric offices in North Carolina, nearly 90% of parents reported seeking ADHD information online (Sage et al., 2018).

Trends in ADHD diagnoses and treatment. We have witnessed a steep increase in the diagnostic prevalence of ADHD in youth from 1997 to 2016 in national data (Xu et al., 2018). The total consumption of four commonly used stimulant medications (i.e., lisdexamfetamine, methylphenidate, amphetamine, methamphetamine) doubled from 2006 to 2016 (Piper et al., 2018). Despite significant advancement in behavioral therapy, such as adaptive interventions, tiered strategies, and collaborative care models (Fabiano & Pyle, 2019; Piper et al., 2018), psychosocial treatment is under-utilized by families of children and adolescents with ADHD (Morrow et al., 2020; Waxmonsky et al., 2019).

Seasonality. Two studies examined seasonal patterns in search queries of ADHD using Google Trends (Ayers et al., 2013; DeVilbiss & Lee, 2014). Ayers et al. (2013) reported a noticeably higher search interest in ADHD in the winter than in the summer in Australia and the United States using Google Trends data from 2006 to 2010. DeVilbiss and Lee (2014) presented annual rises in searches for ADHD in the spring and fall using Google Trends data from 2004 to 2014 in the United States, though, to our knowledge, a closer examination of monthly fluctuations has not been reported. Seasonal patterns in particular may vary by treatment modality. For instance, families may seek information about medications as the school year approaches and about more intensive and time-consuming psychosocial interventions (e.g., the Summer Treatment Program; Pelham et al., 1998) as the summer arrives, pointing to the value of exploring seasonality in disorder-specific and treatment-related searches.

Media impact: Celebrity and pharmaceutical events. Celebrities can strongly influence people's health-related behaviors. In a systematic review, Hoffman and Tan (2015) identified 14 social, biological, and psychological pathways to explain why celebrities influenced health-related behaviors. More recently, there is increasing attention to Google Trends data relating celebrity events to mental health information-seeking, in particular in suicide research (Arendt & Scherr, 2017; Fond et al., 2015; Gunn III et al., 2020; Koburger et al., 2015). The extent to which reported celebrity suicides increase or decrease public risk for suicide remains unclear; however, existing studies support Google Trends as a viable tool to examine the effects of celebrity news on mental health information-seeking (Arendt & Scherr, 2017). In turn, findings may point toward challenges and opportunities online, related to public mental health knowledge, stigma, awareness, and treatment-seeking.

Well-resourced pharmaceutical companies also help shape people's health decisions and treatment-seeking behaviors, largely through public messaging and media campaigns (Hinshaw & Scheffler, 2014). Hinshaw and Scheffler (2014) propose that pharmaceutical companies may be partially responsible for the increase in ADHD diagnoses and medications. Raising mental health awareness is a common strategy in pharmaceutical marketing (e.g., Monica Seles paid by Shires for binge eating disorder and Vyvanse; Thomas, 2015). Shire's "it's your ADHD, own it" campaign – launched on June 20th, 2011 – was among the most successful marketing campaigns, rated as "genius" (top ranking) by L2ThinkTank.com (Schwarz, 2013). Their one-minute videos starring celebrities such as Adam Levine were followed by a screener to assess symptoms and encourage discussions with doctors. To our knowledge, no study has examined the impact of the "Own It" campaign on public information-seeking related to ADHD interventions.

What We Know, What We Don't Know, and the Current Study

Information-seeking is essential across stages of help-seeking: problem recognition, the decision to seek treatment, service selection, and service use (Eiraldi et al., 2006), positioning it well for identifying internet-based opportunities for disseminating empirically supported information. Seeking health information online using search engines like Google is increasingly common. Many youths with suspected or confirmed ADHD diagnoses, and their caregivers, identify the internet as a trusted, primary or preferred source for mental health information (Bussing et al., 2012; Yu et al., 2019). Tools like Google Trends show promise to understand population-level information-seeking patterns of various health conditions (Arendt & Scherr, 2017; Nuti et al., 2014), but limited work has been done to extend Eiraldi et al.'s help-seeking model for understanding online information-seeking of ADHD. Current trends, seasonality, and media impacts related to online searches for ADHD and its treatment remain unknown.

In the current study, we use Google Trends to examine 1) the trends and seasonality of seeking information related to ADHD and 2) the impact of celebrity and pharmaceutical events. First, reflecting upon the upward trends in the prevalence of ADHD diagnoses and medication consumption (Coker et al., 2016; Danielson et al., 2020; Piper et al., 2018; Xu et al., 2018), we present the trends of searching for ADHD and its treatments on the Google website. Second, we hypothesize and test for seasonal patterns based on previous work on National Autism Awareness Month (DeVilbiss & Lee, 2014) and seasonality of mental health disorders (Ayers et al., 2013). Third, we explore the impacts of celebrity announcements and the "Own It" campaign, as both media and pharmaceutical companies are key stakeholders. Findings are interpreted in relation to closing the science-to-public gap in health information.

Method

Data Source

Google Trends relative search volumes. All of Google Trends data points were normalized and scaled, extracted directly from the Google website, available from January of 2004 up till 36 hours before data extraction (Google Inc., 2020). The number of searches performed for a particular term (e.g., "ADHD") is divided by the total number of searches for all topics at a given location and within the specified timeframe, which yields a normalized score. All normalized scores are scaled to have a maximum of 100 (i.e., each data point was divided by the highest normalized and multiplied by 100) on any given plot. Normalized scores range from 0 to 100, called the Relative Search Volumes (RSVs). Given the method of scaling and normalization, RSVs have adjusted for temporal and geographical variations in internet access and population size.

For the current study, we extracted monthly data from January of 2004 to February of 2020 (N = 193 months). The first time series was extracted using the search term "ADHD." RSV = 75 in the first time series means 75% of the highest search proportion month among 193 months. We then extracted three treatment-related time series concurrently with search terms: "ADHD treatment," "ADHD medication," and "ADHD therapy," yielding values relative to one another. In this case, RSV = 75 means 75% of the highest search proportion month of the most popular term (i.e., "ADHD medication" in our study).

Celebrity events. We identified an *a priori* list of seven celebrity events (e.g., Michael Phelps discussed his struggles battling ADHD [Parker-Pope, 2008]) by searching for "celebrity and ADHD" on Google and reviewing Twitter profiles. The scoping search yielded a list of 15 celebrities who talked about their long-standing battles with ADHD publicly. Among the 15 celebrities identified, dates and contents of interviews and news articles of celebrities with close to or more than 1 million followers on Twitter were extracted and included in our final analyses (see Table 1, for event details).

Data Visualization

We plotted historical fluctuations of the RSVs in their respective time-series and added locally weighted scatterplot smoothing (loess) lines to visualize the general trends.

Model Selection

We compared the linear, quadratic, and cubic models for each of the search terms. We fit the trends and examined the best-fitting model from linear, quadratic, and cubic models; lower Akaike information criterion (AIC; Akaike, 1974) indicates better fit (i.e., comparable model fit: ΔAIC < 2; considerably better-fitting: 4 < ΔAIC < 7; full support for better-fitting: ΔAIC > 10) (Burnham & Anderson, 2004).

Data Analysis

Trend and seasonality. We used time-series analyses to examine trends and seasonality (N = 193). $N \geq$ is 50 is deemed appropriate for time-series analyses (McCleary & Hay, 1980). A time series can be decomposed to the trend, seasonal, cyclical, and irregular (random) components (Jebb et al., 2015). The trend component represents the systematic change over time. The seasonal component captures repeating patterns of increase and/or decrease with regards to timing and magnitude. The cyclic component signifies repeating patterns beyond seasonality across irregular time periods (e.g., the economic cycles). As we do not have substantive reasons for long-term cycles in information-seeking related to neurodevelopmental disorders (i.e., cyclic fluctuations beyond one year), cyclic components were not included. The random component represents the leftover variations after all trend, seasonal, and cyclical components are partitioned out, conceptually similar to the error terms in regular regression models. Because the magnitude of monthly fluctuations changes over time, we chose the multiplicative decomposition method over additive decomposition for all time-series models (Jebb et al., 2015).

The impact of nonseasonal events. We used interrupted time-series analyses to examine event-related changes: 1) the impact of celebrity events on RSVs for “ADHD”; 2) the impact of the “Own It” campaign, one of the most successful pharmaceutical marketing campaigns (Schwarz, 2013), on RSVs for “ADHD treatment,” “ADHD medication,” and “ADHD therapy.” After selecting the best-fitting model and accounting for trends and seasonality, we reported 1) the baseline and underlying trend in search interest before an event, 2) immediate change during the month after the event, and 3) the change in linear, quadratic, and cubic terms of the post-event trend as appropriate. We also calculated pre- and post-event descriptive statistics (*M*s and *SD*s).

Results

Searches of "ADHD" Over Time

Data visualization. The patterns of Google searches of ADHD are presented in Figure 1. Search interest in "ADHD" rose over time with seasonal and potentially event-related fluctuations.

Model selection. The quadratic model outperformed the linear and cubic models for searches for "ADHD" (ΔAIC > 10; Table 2).

Trends. The linear, $b = 0.12$, $SE = 0.007$, $t = 16.70$, $p < .01$, and quadratic terms, $b = 0.0010$, $SE = 0.0001$, $t = 6.87$, $p < .01$, were statistically significant, indicating the overall positive trend (linear) with change of rates over time (quadratic), consistent with the subtly noticeable trough prior to the rise demonstrated in Figure 1.

Seasonality. Holiday breaks (i.e., May, June, July, November, December) coincided with decrease in search interest, *p*s < .05, yet post-break periods (i.e., January, February, August, September) overlapped with rise in search interest, *p*s < .05 (Table 3). The largest seasonal factor was for September, $b = 12.80$, $SE = 0.97$, $t = 13.14$, $p < .01$, indicating a peak in searching for "ADHD" online in September. The lowest seasonal factor was for December, $b = -11.71$, $SE = 0.98$, $t = -11.95$, $p < .01$, suggesting a trough in searching for "ADHD" online in December. ADHD Awareness Month (October) coincided with rise of public interest in ADHD, $b = 4.98$, $SE = 0.98$, $t = 5.11$, $p < .01$.

The impact of celebrity events. Descriptive statistics of monthly RSVs before and after celebrity events and inferential statistics from regression models using interrupted series analyses are presented in Table 4. Celebrity events, such as Justin Timberlake's Interview (Weintraub, 2008), the New York Times article about Michael Phelps and ADHD (Parker-Pope, 2008), and the HuffPost blog about Glenn Beck and ADHD (Laskoff, 2009), were associated with post-event baseline (immediate increase in search interest of ADHD in the month following these events), as well as post-event changes in the linear trends, *p*s < .01. Celebrity events, including the blog about Glenn Beck and ADHD (Laskoff, 2009), the HuffPost article about Ty Pennington and ADHD (Gostin, 2012), and Will.i.am admitting to having been diagnosed with ADHD ("Will.i.am Admits To," 2013), are associated with changes in quadratic trends, *p*s < .01. No other significant results were reported for celebrity events impacting post-event baselines, linear trends, or quadratic trends, *p*s > .05.

Searches of "ADHD Treatment," "ADHD Medication," and "ADHD Therapy"

Data visualization. The patterns of treatment-related searches on the Google website are presented in Figure 2. Given the similar rates of searches for "ADHD treatment" and "ADHD medication" before 2008, it is possible that the general public interchangeably used "ADHD treatment" and "ADHD medication" as search terms in earlier years. There was a significant increase in searching for "ADHD medication." Searches for "ADHD therapy" remained relatively low, compared to "ADHD medication" and "ADHD treatment."

Model selection. The linear model outperformed the quadratic and cubic models for the searches for "ADHD treatment" (ΔAIC > 10). For "ADHD medication," the quadratic model was considerably better than the linear model (ΔAIC > 10); the difference between the quadratic model and the cubic model was minimal (ΔAIC = 3) and therefore the more parsimonious quadratic model was selected. For "ADHD therapy," the quadratic model outperformed the linear and cubic models (ΔAIC > 10).

Trends. For "ADHD treatment," the linear term was negative and statistically significant (b = -0.03, SE = 0.005, t = -6.97, p < .01), suggesting a downward trend in using "ADHD treatment" as a search term over time. For "ADHD medication," the linear, b = 0.26, SE = 0.01, t = 26.39, p < .01, and quadratic terms, b = 0.001, SE = 0.0002, t = 6.70, p < .01, were positive and statistically significant, representing an overall upward trend with change in rates over time. For "ADHD therapy," in spite of having smaller magnitude, the linear, b = 0.02, SE = 0.003, t = 6.85, p < .01, and quadratic terms, b = 0.0003, SE = 0.00005, t = 6.01, p < .01, were also positive and statistically significant.

Seasonality. June, November, and December coincided with decreases in searches for "ADHD medication" and "ADHD treatment," ps < .05; on the other hand, February and September were associated with increased searches for "ADHD medication" and "ADHD treatment," ps < .05 (Table 3). The largest seasonal factor was September for searches for "ADHD treatment," b = 6.00, SE = 1.20, t = 4.99, p < .01, "ADHD medication," b = 9.70, SE = 1.76, t = 5.53, p < .01, and "ADHD therapy," b = 1.90, SE = 0.70, t = 2.70, p = .01, indicating peaks in searching for different ADHD-related treatment options online at the beginning of the school year. Peaks in searches for "ADHD treatment," b = 4.25, SE = 1.22, t = 3.49, p < .01, and "ADHD medication," b = 6.37, SE = 1.77, t = 3.59, p < .01, also were detected after the new year, yet such peaks were not detected as a seasonal pattern for searches for "ADHD therapy," $b = 1.20$, $SE = 0.71$, $t = 1.69$, $p = .09$. The lowest seasonal factor was June for searches for "ADHD medication," $b = -8.66$, $SE = 1.74$, $t = -4.96$, $p < .01$, and "ADHD treatment," $b = -5.49$, $SE = 1.19$, $t = -4.60$, $p < .01$, suggesting a trough in searching for "ADHD medications" in summer. The lowest seasonal factor of searching for "ADHD therapy" was for December, $b = -2.98$, $SE = 0.71$, $t = -4.21$, $p < .01$, suggesting troughs in searching for "ADHD therapy" during winter breaks. Again, there was increased searching for "ADHD treatment," "ADHD medication," and ADHD therapy" during October's ADHD Awareness Month, *p*s < .05.

The impact of "Own It" campaign. The impact of the "Own It" pharmaceutical campaign on search patterns of "ADHD treatment," "ADHD medication," and "ADHD therapy" are displayed in Table 5. This campaign did not yield significant immediate impact (post-event baseline) during the month the campaign was initiated, *p*s > .05. Initiating the "Own It" pharmaceutical campaign induced a negative change of linear trend in searching for "ADHD treatment" after the event, $b = -0.08$, $SE = 0.02$, $t = -3.90$, $p < .01$. For "ADHD medication," starting the "Own It" pharmaceutical campaign induced a negative change of linear trend, $b = -0.14$, $SE = 0.05$, $t = -2.73$, $p = .01$, and positive change of the quadratic trend, $b = 0.01$, $SE = 0.001$, $t = 7.69$, $p < .01$. For "ADHD therapy," starting the "Own It" pharmaceutical campaign induced a positive change of linear trend after the event, $b = 0.04$, $SE = 0.02$, $t = 2.66$, $p = .01$; the change of the quadratic trend was not significant, $b = 0.001$, $SE = 0.001$, $t = 1.13$, $p = .26$.

Discussion

We used time-series analyses of Google Trends data to examine search patterns of ADHD disorder- and treatment-related terms, informed by help- and information-seeking models (Eiraldi et al., 2006; Marton & Choo, 2012). To our knowledge, this is the first study to examine temporal and seasonal search trends, as well as relations to celebrity and pharmaceutical events.

Trends

Information-seeking trends align with trends of mental health beliefs, diagnostic prevalence and service utilization (Coker et al., 2016; Danielson et al., 2020; McCleary & Hay, 1980; Piper et al., 2018; Xu et al., 2018). Overall, searches for "ADHD" rose, consistent with the increasing usage of the internet to seek ADHD-related information (Bussing et al., 2007, 2012) and the increasing prevalence of ADHD diagnoses (Danielson et al., 2020; Visser et al., 2014; Xu et al., 2018). Searches for "ADHD treatment" decreased yet searches for "ADHD medication" and "ADHD therapy" increased, perhaps reflecting an increase in specificity of searches for and public knowledge of ADHD treatment (Bussing et al., 2007, 2012). Especially notable, searches for "ADHD medication" increased dramatically in recent years, consistent with the upsurge of psychotropic medication prescription and consumption (Piper et al., 2018)and more widely and publicly accepted neurobiological basis (and, corresponding treatment) for the disorder (Parcesepe & Cabassa, 2013). In contrast, we found searches for "ADHD therapy," despite its statistically significant upward trend, remained relatively low, according to our visual inspection of Figure 2. This finding may be explained by national trends in service utilization: 1) medications are first-line treatments for most children diagnosed with ADHD (Danielson et al., 2018; Visser et al., 2014) and 2) psychosocial interventions are under-utilized (Danielson et al., 2018; Morrow et al., 2020; Waxmonsky et al., 2019).

Seasonality

Our findings on seasonality extend work by Ayer et al. (2013) and DeVilbiss and Lee (2014). Ayer et al. (2013) reported larger seasonal factors in affective disorders than ADHD. Unlike affective disorders for which severity and impairment may vary with sunlight and seasons (Hidaka, 2012; Lambert et al., 2002), ADHD is a neurodevelopmental disorder characterized by symptoms likely to cause the greatest impairments during the school year – when demands for attention and task persistence are high – often leading to academic underachievement (Barkley, 2018). In other words, academic demands coincide with academic calendars, potentially motivating different patterns of information-seeking by parents that associate with the beginning and end of the school year, and for instance, with the timing of exams. Unique to “ADHD therapy,” the large coefficients detected in the fall were not observed during spring, which may reflect the timing of Individualized Educational Plan (IEP) meetings that are typically scheduled at the beginning of the school year. The absence of statistically significant change in search patterns from June to August aligns with a documented lack of (opportunity for) proactive discussions, with mental health professionals, related to medication breaks (Ibrahim & Donyai, 2018) and shortage of evidence-based summer programs at the national level. The peaks in searching for ADHD and its treatment (i.e., searches for “ADHD,” “ADHD treatment,” “ADHD medication,” “ADHD therapy”) every October align with the designation of October as ADHD Awareness Month, a collaborative initiative started in 2004. Similar patterns have been observed for information-seeking during the Breast Cancer Awareness Month (Glynn et al., 2011) and the National Autism Awareness month (DeVilbiss & Lee, 2014). Findings related to seasonality suggest 1) ADHD Awareness Month is an effective public health initiative to increase public interest in ADHD and 2) IEP meetings and other systematically scheduled school events may offer insights into underutilized opportunities to enhance public knowledge of school structures and tiered interventions (Fabiano & Pyle, 2019).

Media Impact: Celebrity and Pharmaceutical Events

Fluctuations in online searches related to ADHD cannot be attributed to one specific celebrity event, consistent with findings that indicate the influence of celebrity events on suicide-related online searches varied with celebrities' popularity (Gunn III et al., 2020). Our findings (of popularity based on Twitter followers) included events of seven very popular celebrities (with close to or more than 1 million followers on Twitter). Thus, we cannot draw conclusions directly linking celebrities' popularity to the magnitude of impact for online information-seeking. Our findings do suggest, however, that celebrity effects are more salient in earlier years, specifically three that occurred between 2008 and 2009, that altogether (and by their proximity to one another) may have increased public awareness of the disorder and its indicated treatments. Perhaps more recent events are less impactful because, during the last decade, ADHD has become more widely known, as evidenced by Bussing et al.'s (2012) report that only around 10% of parents had never heard of ADHD.

Finally, there were no immediate changes in treatment-related searches during the month following the launch of the "Own It" pharmaceutical campaign. An examination of corporate motivations and industry contexts may help to explain this unanticipated finding. The impact of pharmaceutical marketing on online information-seeking may be medication-specific to encourage interest in medications produced by the manufacture sponsor, rather than all ADHD medications, as evidenced by Shire's sale record in 2011 (having outpaced the 10% growth of the US ADHD medication market) (Shire pharmaceuticals, 2012). Although pharmaceutical campaigns are motivated by financial incentives, they may increase public awareness, interest, and knowledge of ADHD, evidenced by a decrease in linear trends of "ADHD treatment," as well as a negative change in linear trend yet positive quadratic change of "ADHD medication." Possibly, more searches are driven by extracting and verifying medication-specific information, rather than exploratory browsing (see Wilson, 1999 for definitions of browsing, extracting, and verifying in information behavior research). Notably, the post-campaign change in searching for "ADHD therapy" showed the opposite pattern (i.e., a small positive change in the linear trend). Altogether then, the "Own It" campaign may have contributed to raising interest and awareness about Shire's ADHD medications, but not to generating knowledge of ADHD therapy more broadly.

Limitations and Future Direction

Findings warrant caution due to study limitations. First, similar to other health-related studies using Google Trends (Arora et al., 2019; Mavragani et al., 2018; Nuti et al., 2014), data prior to 2004 are not available. Thus, we are not able to examine the impact of events before 2004, such as the release of Concerta and the initiation of the Multimodal Treatment of ADHD Study (MTA Cooperative Group, 1999). However, it is worth noting that only 5% of parents and adolescents reported the internet as their primary source for information about ADHD in a community sample in 1998 (Bussing et al., 2007) and Google did not become the default search engine for Yahoo!, one of the most common directory websites in the 1990s, until June of 2000 (Google News, 2000**).**

Second, our results cannot be extrapolated to any specific subpopulation. Although Google Trends data represent all types of searches conducted related to ADHD on Google – including those of patients, caregivers, providers, and teachers – we speculate, based on prior findings (Kubb & Foran, 2020), that a large proportion of searches may come from parents of children with suspected or confirmed ADHD diagnoses. Notably, despite the closing gap in access to smartphones (Pew Research Center, 2019), individuals from disadvantaged socioeconomic backgrounds still may be under-represented in search engine data (especially the first decade of data); for example, individuals who are younger with higher education and higher internet skills are more likely to seek health information online (Chen & Zhu, 2016; Jacobs et al., 2017).

Third, we did not include the full universe of search terms that may be used to browse the internet for information about ADHD, which may have excluded some individuals with low psychological literacy or others that prefer to avoid diagnostic labels. Recall Bussing et al.'s (2012) findings that most parents and adolescents (93% and 98%, respectively) in a community sample had heard about ADHD. Although the term "ADHD" is well-known, some may search instead for symptoms (e.g., "impulsivity"), functional deficits (e.g., "failing school") and/or solutions (e.g., "parenting strategies") (Yu et al., 2019). Future studies of search engine data may benefit from including terms that reflect transdiagnostic language or common elements approaches; details of the Distillation and Matching Model (Chorpita et al., 2005).

Fourth, our population-level Google RSVs do not afford us the opportunity to examine individual-level predictors and processes. Help-seeking models (Eiraldi et al., 2006) suggest racial/ethnic and socioeconomic variations in cultural beliefs, psychological literacy, and mental health stigma as potential mediators and moderators (Turner et al., 2015). Problem recognition and online mental health information-seeking do not often lead to seeking professional help; for instance, in a recent study from China, among parents who both suspected their child might have ADHD and searched online for information about the disorder, fewer than one-third sought a professional evaluation (Yu et al., 2019). Future research may benefit from a closer examination of individual predictors related to information access and need at each stage of help-seeking (Eiraldi et al., 2006) including attention to cost-benefit analyses (Goldsmith et al., 1988).

Finally, the present examination of media influence was limited to seven celebrities based on an arbitrary cutoff of one million Twitter followers and one pharmaceutical campaign. The small sample size limited our ability to examine event features more closely (e.g., prominence of the celebrity, racial/ethnic background, channels of media release) that may influence public information-seeking patterns. Regarding the "Own It" campaign specifically, Adam Levine's video aired until January 15th, 2017 (more than five years since its launch date) and remains available on YouTube and other channels. It is unknown how long it takes a pharmaceutical campaign to influence information-seeking behaviors. In the current study, we defined the launching month (June 2011) as the event in our interrupted time-series analyses to avoid the potential confounding influence of subsequent events. Future studies can benefit from incorporating theoretical frameworks across fields (Hoffman & Tan, 2015) and examine the “active ingredients” of celebrity and pharmaceutical events, such as the content of the videos, features of the websites, involvement of influential celebrities, intentions of the celebrities (i.e., blaming or advocating for ADHD), and structure of incentive systems, that can influence information-seeking patterns, along with prescribing decisions, treatment preferences, and/or service uptake.

Policy and Clinical Implications

Findings point to opportunities for improving information dissemination. Upward trends in searching for ADHD over time and increased specificity in information-seeking related to treatment (from “ADHD treatment” to “ADHD medication” and “ADHD therapy”) may reflect progress in advocacy and treatment development (Hinshaw & Scheffler, 2014). Policymakers can help frame public discourse by drafting guidelines detailing what is allowed and not allowed for online marketing, emphasizing the importance of functional assessment, above and beyond “scrutinizing” research to approve *safe* and *effective* treatments. Additionally, policymakers can allocate resources toward mental health advocacy, such as ADHD Awareness Month to reduce stigma (see Parcesepe & Cabassa, 2012, for recommendations related to anti-stigma) and raise awareness about existing resources (Pilapil et al., 2017). Involving racial/ethnic minority celebrities in public health initiatives may be particularly helpful in reaching families of color. In a focus group study of African American adults, many described celebrities as credible sources of mental health information, and celebrity effects are perceived stronger when the participants and the celebrity share the same racial/ethnic backgrounds (Mishra et al., 2009).

Effective dissemination requires evidence-based information to be both distributed and consumed. Existing studies indicate that 1) a vast amount of information about ADHD online is misleading, conflicting, and hard to digest (Ahmed et al., 2014; Yu et al., 2019) and 2) websites with empirically supported information are not necessarily clicked and consumed even when displayed (Rosenblum & Yom-Tov, 2017). To improve the quality of information on the internet, Youngstrom and Cotuna (2020) have started to develop Wikipedia pages via the Helping Give Away Psychological Science initiative. A next step may include efforts toward improving e-health literacy, which relies on six domains (traditional, information, media, health, scientific, computer) (Norman & Skinner, 2006). Standard guidelines, for example by the Stanford Persuasive Tech Lab (Fogg, 2002) and the Health on the Net Foundation (Boyer, Gaudinat, Baujard, & Geissbühler, 2007), support developers to improve website quality and provide with tools (for health care providers and consumers) to evaluate health information online; however, not every consumer is aware of or prepared to apply these guidelines, due to disparities in e-health literacy.

Healthcare professionals should share the responsibility for guiding patients to seek and consume mental health information on the internet, in particular because they are often perceived as the most trusted and reliable information source (Gray et al., 2005; Jacobs et al., 2017; Mishra et al., 2009), especially by parents of youths with suspected or confirmed diagnoses of ADHD (Bussing et al., 2012; Rosenblum & Yom-Tov, 2017; Sciberras et al., 2010). Discussing health information presented online in an open, respectful and culturally sensitive manner can also improve patient-provider relationships (Tan & Goonawardene, 2017). Thus, increasing social and cultural responsiveness in disseminating empirically supported information online, in comprehensible terms, should be a universal research and training goal for mental health professionals. We hope this paper can help 1) initiate a research agenda to improve the speed and reach of scientific communication and 2) provide a roadmap for leveraging internet search patterns to improve policy and clinical practices.

Tables and Figures

Table 1. *Celebrities and Attention-Deficit Hyperactivity Disorder*

	Celebrity	Event Date	Interview or article title	Source	Followers[a]
1	Justin Timberlake	6/16/08	The Love Guru	Collider	64.4
2	Michael Phelps	11/24/08	Michael Phelps and the Potential of A.D.H.D.	NYT	2.0
3	Glenn Beck	11/21/09	Glenn Beck for Governor	HuffPost	1.2
4	Ty Pennington	2/21/12	‘Revolution’ Host Ty Pennington Talks Lifelong Battle with ADHD	HuffPost	0.98
5	Will.i.am	4/29/13	Will.i.am Admits to Suffering from ADHD: "It works well for me"	Capital FM	12.5
6	Adam Levine	2/24/14	Talks ADHD Symptoms: “I Really Can’t Pay Attention.’	Inquisitr	8.3
7	Channing Tatum	10/14/14	Channing Tatum: A Work in Progress	NYT	8.1

Note. [a] We retrieved the number of Twitter followers in millions on June 30th, 2020. ADHD = attention-deficit hyperactivity disorder. NYT = New York Time

Table 2. *Comparison of Fit Indices in Models that Examine Trends of RSV*

Models	*df*	AIC	BIC	LL	Comparison	LR	*p*
ADHD							
Linear	3	1247.20	1256.95	-620.60			
*Quadratic	4	1225.46	1238.44	-608.73	linear vs. quadratic	23.74	< .01
Cubic	5	1248.64	1264.85	-619.32	quadratic vs. cubic	21.19	< .01
ADHD treatment							
*Linear	3	1080.42	1090.18	-537.21			
Quadratic	4	1094.07	1107.05	-543.03	linear vs. quadratic	11.64	< .01
Cubic	5	1117.83	1134.04	-553.91	quadratic vs. cubic	21.76	< .01
ADHD medication							
Linear	3	1381.82	1391.58	-687.91			
*Quadratic	4	1358.52	1371.51	-675.26	linear vs. quadratic	25.30	< .01
Cubic	5	1361.68	1377.89	-675.84	quadratic vs. cubic	1.16	0.28
ADHD therapy							
Linear	3	872.13	881.89	-433.07			
*Quadratic	4	858.72	871.70	-425.36	linear vs. quadratic	15.42	< .01
Cubic	5	884.18	900.39	-437.09	quadratic vs. cubic	23.46	< .01

Note. *df* = degree of freedom; AIC = Akaike information criterion; BIC = Bayesian information criterion; LL = Log likelihood; LR = likelihood ratio. RSV = Relative Search Volume.

Table 3. *Seasonality (Monthly Fluctuations) of Online Searches of ADHD and its Treatment*

	ADHD			ADHD Medication			ADHD Therapy			ADHD Treatment		
	b	*SE*	*t*	*b*	*SE*	*t*	*b*	*SE*	*t*	*b*	*SE*	*t*
January	2.21*	0.98	2.25	2.37	1.77	1.34	0.14	0.71	0.20	-1.13	1.21	-0.93
February	7.33 **	0.98	7.44	6.37**	1.77	3.59	1.20	0.71	1.69	4.25**	1.22	3.49
March	0.49	0.96	0.51	1.48	1.73	0.85	0.47	0.70	0.67	-1.36	1.19	-1.15
April	1.24	0.96	1.28	1.35	1.74	0.78	0.28	0.70	0.40	1.07	1.19	0.90
May	-8.02**	0.97	-8.29	-7.65**	1.74	-4.40	-2.54**	0.70	-3.63	-5.49**	1.19	-4.60
June	-10.71**	0.97	11.06	-8.66**	1.74	-4.96	-0.79	0.70	-1.13	-1.87	1.20	-1.56
July	-2.58*	0.97	-2.66	0.09	1.75	0.05	-0.29	0.70	-0.41	-1.81	1.20	-1.51
August	5.29**	0.97	5.44	3.21	1.75	1.83	-0.29	0.70	-0.41	0.25	1.20	0.21
September	13.28**	0.97	13.63	9.70**	1.76	5.53	1.90*	0.70	2.70	6.00**	1.20	4.99
October	4.09**	0.98	4.19	3.64*	1.76	2.07	1.65*	0.71	2.33	4.00**	1.21	3.32
November	-3.85**	0.98	-3.93	-4.87*	1.76	-2.76	0.14	0.71	0.20	-1.56	1.21	-1.29
December	-11.16**	0.98	11.39	-8.31**	1.77	-4.70	-2.98**	0.71	-4.21	-4.50**	1.21	-3.72

Note. ADHD = attention deficit hyperactivity disorder. *SE* = Standard Errors. $*p < .05$. $**p < .01$

Table 4. *The Impact of Celebrity Events on Searches of ADHD*

Events	Pre-event	Post-event	Pre-event						Post-event								
			Baseline			Trend			Baseline			Change in linear trend			Change in quadratic trend		
	M(SD)	*M(SD)*	*B*	*SE*	*t*	*B*	*SE*	*t*	*B*	*SE*	*t*	*B*	*SE*	*t*	*B*	*SE*	*t*
1	60.88(5.09)	70.63(8.42)	66.29**	1.58	42.07	-0.23**	0.04	-5.29	5.98**	1.87	3.21	0.38**	0.05	8.08	0.0004	0.0003	1.28
2	60.79(4.96)	71.03(8.29)	65.31**	1.52	42.94	-0.19**	0.04	-4.77	6.30**	1.86	3.38	0.32**	0.04	7.61	0.0005	0.0003	1.43
3	60.19(4.78)	72.38(7.38)	62.80**	1.27	49.29	-0.15**	0.03	-5.41	13.45**	1.71	7.88	0.20**	0.03	5.95	0.0018**	0.0004	4.66
4	62.60(7.25)	73.35(6.68)	57.22**	1.22	47.05	0.07**	0.02	3.48	3.64	2.05	1.78	-0.05	0.05	-0.96	0.0035**	0.0008	4.23
5	63.27(7.08)	74.26(6.71)	57.35**	1.11	51.89	0.08**	0.01	4.88	2.95	2.12	1.39	-0.09	0.07	-1.32	0.0049**	0.0012	4.06
6	63.74(7.03)	74.84(6.86)	57.70**	1.05	54.87	0.08**	0.01	5.83	0.74	2.21	0.33	-0.04	0.08	-0.52	0.0049**	0.0016	3.05
7	64.49(6.82)	77.28(6.50)	58.71**	0.95	61.94	0.08**	0.01	6.92	-0.19	2.55	-0.08	0.12	0.16	0.75	0.0042	0.0038	1.11

Note. *M* = Mean. *SE* = Standard error. Event 1: 6/16/08 Justin Timberlake's interview –The love guru (Collider); Event 2: 11/24/08 Michael Phelps and the Potential of A.D.H.D. (New York Times); Event 3: 11/21/09 Glenn Beck for Governor (HuffPost); Event 4: 2/21/12 Revolution' Host Ty Pennington Talks Lifelong Battle With ADHD (HuffPost); Event 5: 4/29/13 Will.i.am Admits to Suffering from ADHD: "It works well for me" (Capital FM); Event 6: 2/24/14 Adam Levine Talks about ADHD Symptoms, 'I Really Can't Pay Attention' (Inquisitr); Event 7: 10/14/14 Channing Tatum: A Work in Progress. (New York Times).
$^{*}p < .05$. $^{**}p < .01$

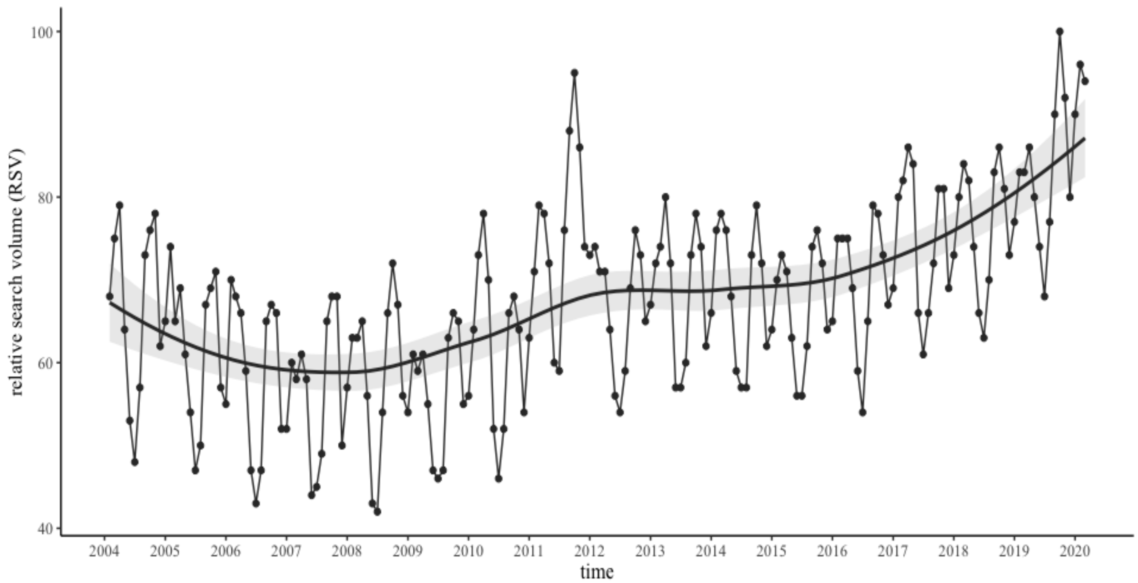
Table 5

The Impact of the "Own It" Campaign on Searches of "ADHD Treatment," "ADHD Medication," and "ADHD Therapy"

Search term	Pre-event	Post-event	Pre-event						Post-event								
			Baseline			Trend			Baseline			Change in linear trend			Change in quadratic trend		
	M(SD)	*M(SD)*	*B*	*SE*	*t*	*B*	*SE*	*t*	*B*	*SE*	*t*	*B*	*SE*	*t*	*B*	*SE*	*t*
ADHD treatment	27.27 (4.77)	23.60 (0.99)	6.16**	0.79	33.20	0.02*	0.02	1.63	-2.2	1.06	-2.00	-0.08**	0.02	-3.90	--	--	--
ADHD medication	35.46(10.10)	57.54 (14.51)	19.08**	1.57	12.20	0.25**	0.03	9.17	0.93	2.45	0.38	-0.14*	0.05	-2.70	0.01**	0.001	7.69
ADHD therapy	9.38(2.79)	11.03 (1.78)	9.80**	0.49	20.00	-0.01*	0.01	-1.7	0.54	0.76	0.70	0.04*	0.02	2.66	0.001	0.001	1.13

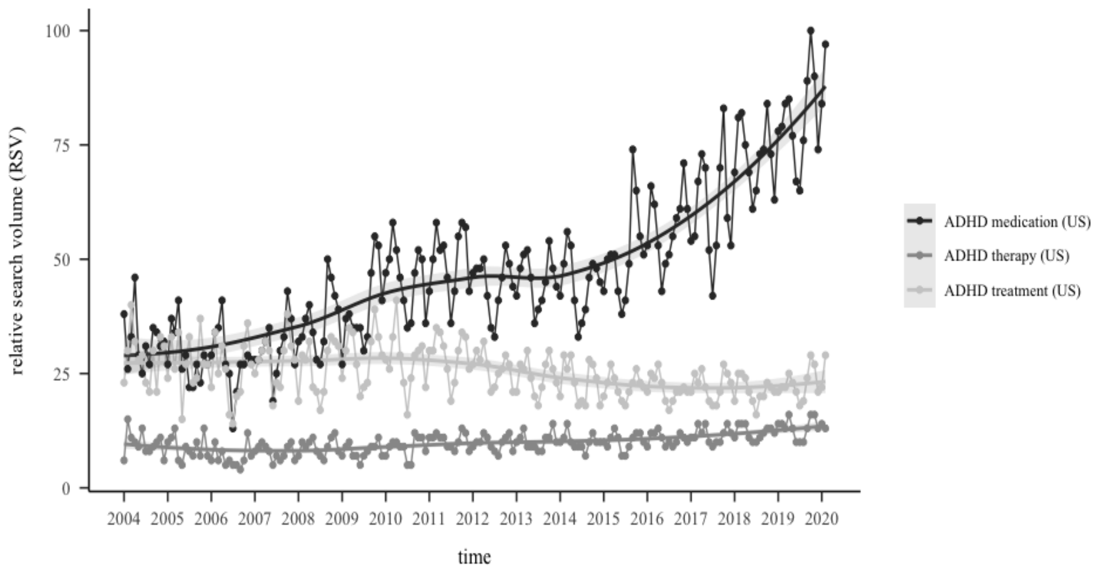
Note. *M* = Mean. *SE* = Standard error. **p* <.05. ***p* < .01

Figure 1. *Google Trends Relative Search Volumes for Attention-Deficit Hyperactivity Disorder (ADHD).*



Note. We extracted monthly for January 2004 to February 2020 using search term "ADHD." We used Locally weighted smoothing (LOESS) to create a smooth line to visualize the general temporal trend. Trend line represents quadratic polynomial regression. $N = 193$.

Figure 2. *Google Trends Relative Search Volumes for "ADHD Treatment," "ADHD Medication," and "ADHD Therapy."*



Note. We extracted monthly data with three treatment-related search terms: "ADHD treatment," "ADHD medication," and "ADHD therapy" concurrently, yielding values relative to each other, for January 2004 to February 2020. We used Locally weighted smoothing (LOESS) to create a smooth line to visualize the general temporal trends. Trend line represents quadratic polynomial regression. *N* = 193. ADHD = attention-deficit hyperactivity disorder.

III. STATE VARIATION IN ONLINE INFORMATION SEEKING ABOUT ADHD

This manuscript has been submitted to Journal of Attention Disorders; thus, it adheres to APA 7th Edition formatting guidelines for consistency in this dissertation.

Zhao, X., Wu, W., Timmons, A., & Frazier, S. L. (Under Review). State variation in online information seeking about ADHD.

Authors' note: This research was supported in part by an FIU Graduate School Dissertation Year Fellowship awarded to Xin Zhao.

Abstract

Objective. Geographical variations in mental health service utilization are large. The present study examined geographical variation in online information seeking, and inequalities related to information and care, for ADHD. *Methods*. State-level relative search volumes (RSV) using “ADHD,” “ADHD treatment,” “ADHD medication,” and “ADHD therapy” were extracted from Google Trends and 40 state-level predictors from publicly available sources in 2018. Visualizations of state variations in online information seeking related to ADHD on Google and correlation coefficients between information seeking and service utilization at the state level were presented. Two supervised learning models— random forest and elastic net—for state-level RSVs of each search term were used to select relatively important variables to explain search interest. This study used leave-1-out cross-validation as a validation method. *Results.* State-level RSVs of “ADHD” and “ADHD medication” reflected ADHD diagnoses (mild, moderate/severe, and all ADHD diagnoses) and service utilization (percentage of youth taking medications for ADHD, percentage of youth having ADHD and receiving behavior therapy). Machine learning algorithms suggested that seeking ADHD-related information online was relatively more important in states with a higher percentage of underserved families (e.g., youth with special needs, families receiving supplemental security income, and Hispanic/Latinx youth) and/or with more families who are already connected to systems of care (e.g., youth with ADHD diagnoses or treatment). *Conclusions.* Findings highlight internet-based opportunities for understanding and detecting inequalities in need for and access to empirically supported information and care.

Keywords**:** ADHD, state variation, machine learning, random forest, elastic net

Literature Review

Geographical variation in service utilization corresponds to well-documented inequities in mental health need and care (Cook et al., 2019). The internet is a widely accessible (https://www.statista.com/statistics/184691/internet-usage-in-the-us-by-state/) and popular source for health information among parents (Kubb & Foran, 2020) and online information seeking may influence decision-making related to seeking, selecting, and utilizing services for mental health concerns (Zhao et al., under review). Most studies on information-seeking behaviors are limited to one state (Bussing et al., 2007, 2012), and information equity in mental health is understudied. We present state-level variation in Google Trends data for attention-deficit/hyperactivity disorder (ADHD).

Geographical Variation in ADHD Diagnoses, Treatment, and Information-Seeking

ADHD incurs long-term impairments (Barkley, 2018; Gordon & Fabiano, 2019) and substantial societal burden (Doshi et al., 2012). Despite advances in evidence-based practice for ADHD (Pelham, Jr. et al., 2005; Schatz et al., 2020), large variation in ADHD diagnoses and treatment is documented at county, state, regional, and national levels (Danielson et al., 2018; Fulton et al., 2009, 2015; McDonald & Jalbert, 2013; Visser et al., 2014, 2015). At the state level, 2011 National Survey of Children's Health (NSCH) revealed a threefold difference in ADHD diagnoses and a fivefold difference in use of ADHD medication (Visser et al., 2015). Data from US pharmacies in 2008 revealed even wider variations: a 14-fold difference among youth and a sixfold difference among adults treated by stimulant medications (McDonald & Jalbert, 2013). Traditional correlation and regression analyses revealed sociodemographic (Huber et al., 2018), provider (Fulton et al., 2015; McDonald & Jalbert, 2013), policy and funding variables

(Bokhari & Schneider, 2011; Fulton et al., 2015; Morrill, 2018) contributed to state variation in ADHD diagnoses and treatment.

Sociodemographic and clinical profiles. Racially/ethnically minoritized groups were historically less likely to be diagnosed with and treated for ADHD (Coker et al., 2016; Fulton et al., 2009; Huber et al., 2018; McDonald & Jalbert, 2013). Diagnostic prevalence correlated negatively with percentages of Hispanic youth residents (Huber et al., 2018). County-level analyses revealed higher pediatric stimulant prescriptions among populations with less education and higher poverty (McDonald & Jalbert, 2013). ADHD incurs financial and occupational impairments to individuals (Barkley, 2018) and caregivers (Zhao et al., 2019), indicating need for further understanding roles of income and employment. Health insurance coverage was a salient predictor for receiving psychosocial treatment in 2016–2017 NSCH (Morrow et al., 2020).

Providers. Providers' impact on diagnoses and treatment varies by specialty and age groups (Fulton et al., 2009; McDonald & Jalbert, 2013). Most youth received ADHD diagnoses from pediatricians, while most adults were diagnosed by psychiatrists or family medicine practitioners (McDonald & Jalbert, 2013). In early 2000s, availability of older physicians (age ≥45) was associated with lower medication prescriptions; such relations were more salient among pediatricians yet displayed oppositely among psychiatrists (Fulton et al., 2009). Consistent with earlier findings, rates of children receiving stimulant medications positively correlated with supply of pediatricians in 2008 (McDonald & Jalbert, 2013).

Policies and funding. Legislation, policies and funding contribute to state variation in service utilization, disproportionally impacting youth from low-income families and public schools (Caye et al., 2020; Graaf & Snowden, 2020; Morrill, 2018). For instance, state legislations vary in age requirements for school entry; relatively younger ages were associated with ADHD diagnoses (Caye et al., 2020). Medicaid waivers may reduce financial barriers to care; however, according to state officials, budgetary constraints were common considerations for not adopting Medicaid waivers (Graaf & Snowden, 2020). Additionally, 1.2 million youth received supplemental security income (SSI) in 2008 (quadrupled from 1990), demonstrating substantial growth in need for resources (Sevak & Bruns, 2018). Notably, positive relations between SSI and ADHD diagnoses were more salient in the South (Schmidt & Sevak, 2017), corresponding to higher diagnostic prevalence (Fulton et al., 2009; McDonald & Jalbert, 2013).

Digital divide. Although the internet is widely available, digital skills and cultures are important to consider for understanding the digital divide (Scheerder et al., 2017). Adults identifying as older, with lower educational level, from racially minoritized backgrounds, and without broadband internet are less likely to search health information online (Kim et al., 2021; Massey, 2016). Access to broadband internet and policies supporting equitable computer science education vary across states, adding complexities to information equity. Survey studies revealed variation in the percentage of parents and teachers reporting the internet as an important source for ADHD-related information (Akram et al., 2009; Bussing et al., 2012; Sage et al., 2018). Despite differences in methodology and samples, these studies provide preliminary evidence for geographical inequity.

Big Data Tools Can Identify Geographical Variation in Information-Seeking

Google Trends data point to geographical variation related to online information-seeking in developed countries (Arora et al., 2019; Mavragani et al., 2018). For instance, Google Trend analyses with key words “prostate cancer” and “prostate biopsy” revealed that search interest was highest in South Carolina and lowest in Hawaii (Rezaee et al., 2019), highlighting uneven geographical distribution of search interest as well as the potential and need for understanding equitable care. Machine learning algorithms can distill the relative importance of a large number of related variables (Cohen et al., 2020; Hastie et al., 2009). Compared to models that make classical statistical inferences, machine learning models enable analyses of correlated predictors with non-linear relationships.

Present Study

Large geographical variations in service utilization indicate a need for looking beyond individual patients to state-level patterns. We examined geographical variation specific to online information seeking related to ADHD. We hypothesize 1) search interest will vary across states and by search terms; 2) search interest will reflect patterns of diagnoses and service utilization; 3) state-level features will predict interest in different keywords.

Method

Data from public repositories do not require approval from Institutional Review Board or collection of informed consent. We extracted, integrated, and analyzed data in R 4.0.3 (R Core Team, 2020).

Data Extraction

Information seeking. Our measures of information seeking included relative search volumes (RSVs) for "ADHD," "ADHD treatment," "ADHD medication," and "ADHD therapy" in 2018. We extracted state-level RSVs for 50 states and Washington DC (hereafter, N=51) from Google Trends (https://trends.google.com/trends/?geo=US). They represent the scaled proportion of searches containing a specified (set of) search term(s). State-level RSVs represent the number of searches containing one of the four ADHD search terms divided by the number of all searches *within each state* and scaled in relevance to all other states. RSVs account for differences in internet access and population size, ranging from 0 to 100; the state with the highest search interest out of all states has an RSV=100.

ADHD diagnoses and treatment. We extracted ADHD diagnoses (percentage of children who "currently have ADD/ADHD"), mild ADHD diagnoses (percentage of children with "mild current ADD/ADHD"), moderate/severe ADHD diagnosis (percentage of children with "moderate or severe ADHD"), use of ADHD medications (percentage of children "currently taking medication for ADD/ADHD"), and use of behavior therapy (percentage of children "who currently have ADHD and receive behavioral treatment") from 2018 NSCH.

Other predictors. Preliminary selection was based on 1) availability of state-level data for 2018 *and* 2) they were identified in literature as factors related to ADHD diagnosis, treatment or online health information seeking. We identified variables in domains of sociodemographic profiles, provider characteristics, policies, funding, and digital divide. Because direct measures of digital divide (Scheerder et al., 2017) are unavailable at the state level, we included percentage of population with broadband internet and mandatory K–12 computer science education. See Appendix 1 for details.

Data Analyses

Correlation. Relative comparisons among states were more meaningful than the absolute scale of RSVs; therefore, we computed Kendall's rank correlation (Kendall, 1938) between ADHD service utilization and RSVs at the state level. Kendall's τ accounts for tied ranks and small Ns.

Variable selection. Variable selection means the selection of independent variables. We identified the most important predictor(s) of state-level interest in "ADHD," "ADHD treatment," "ADHD medication," and "ADHD therapy" using two supervised algorithms: elastic net regularization (ENet) and random forest (RF).

Elastic net regularization. The elastic net combines the ridge regression and least absolute shrinkage and selection operator (LASSO) penalties to allow effective regularization and feature selection simultaneously (Hastie et al., 2009). Alphas represent the degree of mixing between ridge (α = 0) and lasso (α = 1), with $0 \leq \alpha \leq 1$ in elastic net analyses. λ is a parameter used to penalize overfitting, ranging from 0 (resulting in the OLS estimators) to infinity (resulting in a model with only one constant). We selected α and λ coefficients using the tuning grid in the "caret" package (Kuhn, 2008) ; each combination of α (from 0 to 1 by .05) and λ (from 0 to 5 by 0.05) was tested to select the optimal tuning parameters that yielded lowest Root Mean Square Error (RMSE). With the optimal α and λ, we used the "glmnet" package to fit the model (Friedman et al., 2010).

Random forest. Random forest is a tree-based ensemble learning method, which allows a large number of correlated input features. We used the recursive feature elimination (RFE) approach, which is a backward selection. We used “rfe” function in the “caret” package to run the models (Kuhn, 2008). The final model was selected based on minimal RMSE; changes in RMSE as the number of selected variables increases in each model are also presented via graphics.

We entered state-level RSVs as the output feature (dependent variable) and 40 predictors as input features (predictors) for each search term; each state is an observation. We used leave-one-out cross-validation approach to select tuning parameters and variables. Variables selected in both models are identified as relatively important variables.

Results

Does Online Information Seeking Vary by State?

We presented state variation in searches for “ADHD (Figure 1a),” “ADHD treatment (Figure 1b),” “ADHD medication (Figure 1c),” and “ADHD therapy (Figure 1d)”. State-level search interest in “ADHD” was highest in West Virginia and Oregon and lowest in Nevada and New Mexico. Search interest in “ADHD treatment” was highest in Oregon, followed by West Virginia and lowest in Colorado, Nevada, California, and New Mexico. A total of 13 states displayed missing RSVs (grey areas) for “ADHD treatment.” Search interest in “ADHD medication” was highest in Maine and Arkansas and lowest in Nevada and Hawaii. Wyoming displayed missing RSV for “ADHD medication.” Search interest in “ADHD therapy” was highest in Massachusetts, Michigan, and Louisiana, and lowest in Tennessee and Arizona. A total of 22 states displayed missing RSVs for "ADHD therapy." We coded missing values as zeroes, as they indicated very low search interest.

Does Search Interest Reflect Patterns of Diagnoses and Service Utilization?

State-level RSVs for "ADHD" correlated positively with prevalence for ADHD diagnoses (τ=.35, p<.001), mild ADHD diagnoses (τ=.19, p=.050), moderate or severe diagnoses (τ=.33, p<.001), use of medication for ADHD (τ=.35, p<.001), and receipt of behavioral therapy (τ=.33, p<.001). Similarly, state-level RSVs for "ADHD medication" correlated with prevalence for ADHD diagnoses (τ =.41, p<.001), mild ADHD diagnoses (τ=.23, p=.019), moderate/severe diagnoses (τ =.40, p<.001), use of medication for ADHD (τ=.48, p<.001), and receipt of behavioral therapy (τ=.32, p=.001). State-level RSVs for "ADHD treatment" correlated with prevalence of mild ADHD diagnoses (τ=.22, p=.032), medication use for ADHD (τ=.27, p=.007), and receipt of behavioral therapy (τ=.20, p=.042), but not for overall ADHD diagnoses or moderate/severe diagnoses, *p*s>.05. RSVs for "ADHD therapy" did not correlate with ADHD diagnoses or treatment, *p*s>.05.

Do Different State-level Features Predict Interest in Different Search Terms?

Table 2 displays regression coefficients for ENet models. Figure 2 illustrates changes in RMSE as the number of predictors retained in RF increased for "ADHD," "ADHD treatment," "ADHD medication," and "ADHD therapy," suggesting the optimal number of predictors in RF. For "ADHD" (α=1, λ=0, *RMSE* =7.38, R^2=.29, *MAE*=5.65), all variables were selected. RF suggested retaining five variables, including percentages of ADHD diagnosis, special care needs, moderate/severe ADHD, Hispanic/Latinx and non-Hispanic White. For "ADHD treatment" (α=1, λ=4.39, *RMSE*=17.29, R^2=.49, *MAE*=12.10), SSI payment per recipient and public health funding were retained in ENet. RF yielded the same predictors. For “ADHD medication” (α=.45, λ=1.82, *RMSE*=14.18, R^2=.29, *MAE*=9.82), fourteen variables were retained in ENet. RF yielded two predictors, proportions of children with special care needs and children taking medications for ADHD, both of which were selected by ENet. For “ADHD therapy” (α=1, λ =4.39, *RMSE*=33.92, R^2=.29, *MAE*=28.69), six variables were retained in ENet. RF suggested two predictors as optimal. Both models selected SSI payment per recipient for “ADHD therapy.”

Discussion

Online information seeking related to ADHD was indicative of diagnoses and treatment use, yet similar results were not reported for search interest in “ADHD therapy.” Seeking ADHD-related information online was more important in states with more families of underserved youth and/or with more families who are connected to care.

Online Information Seeking Vary by State

Findings may be traced to community outreach efforts in areas with major healthcare systems, such as the Oregon Health and Science University Center for ADHD (opened in 2019) that sparked media coverage and, perhaps, searches for ADHD. Except for Oregon, lower interest in ADHD-related information reflected lower prevalence of ADHD diagnoses in the West (Visser et al., 2014, 2015). States with more youth with ADHD diagnoses (e.g., West Virginia: 16%) displayed relatively high search interest in ADHD and ADHD treatment. Specific to medication, search interest was high in Maine and low in Nevada, corresponding to their difference in state averages of methylphenidate consumption in 2016 (Piper et al., 2018). Specific to therapy, missing data might reflect very low search interest in most sparsely populated states.

Access to clinical research and care may not always motivate online information-seeking behaviors. For example, Hawaii, a state with large-scale initiatives to improve youth mental health system of care (Nakamura et al., 2014), did not display high search interest in any ADHD search term. Possibly, these initiatives were not only for ADHD, and thus did not trigger more interest in ADHD compared to other topics (recall RSVs reflect relative interest rather than search volumes). Specific to medication, results were consistent with lower stimulants per capita reported in Hawaii (Piper et al., 2018). More importantly, we propose parabola-shaped relations between information need and access. Accordingly, access to information may increase to an optimal point that increases desire for information and thereby motivates searching; however, increased access to information may lead to saturation (e.g., "I know enough") or confusion (e.g., "My head is swimming") that tempers searching, thereby forming an *inverted-U curve*.

Search Interest Reflected Patterns of Diagnoses and Service Utilization

Search interest in "ADHD" and "ADHD medication" reflected service utilization consistent with our hypotheses. Findings also echoed results of survey studies that demonstrated need for disorder-specific *and* treatment-related information (with medication as a commonly sought and provided treatment modality) (Akram et al., 2009; Sage et al., 2018). Notably, search interest in "ADHD treatment" correlated with percentage of mild (but not moderate/severe) diagnoses. Youth diagnosed with moderate/severe ADHD are more likely to receive medications (~70% to 90%) compared to those with mild ADHD (~60%) (Visser et al., 2015); possibly, elevated impairment motivates searching for medications explicitly rather than treatment options broadly. Inconsistent with hypotheses, search interest in “ADHD therapy” did not correlate with service utilization; note, a large number of states displayed very low search interest, leading to low data variability. Consistent with prior work (Zhao et al., under review), search interest in “ADHD therapy” has been low compared to “ADHD medication.” Low search interest does not represent low information need; instead, populations residing in such areas may have low psychological literacy, suggesting an opportunity for community outreach.

Different State-Level Features Predicted Search Interest in Search Terms

Based on our literature review on state variation in service utilization, we utilized forty empirically supported state-level predictors. Findings revealed that sociodemographic factors and current status of diagnoses and medication helped explain state variation in online search interest in ADHD. Results related to race/ethnicity were consistent with state-level correlation analyses for ADHD diagnostic prevalence (Coker et al., 2016; Huber et al., 2018), service utilization (Huber et al., 2018), and health information-seeking patterns (Kim et al., 2021; Massey, 2016). Latinx adults were less likely than non-Hispanic White adults to seek health information online (Kim et al., 2021; Massey, 2016) and Latinx youth were less likely to receive ADHD diagnoses (Coker et al., 2016).

Public health funding and SSI payment per recipient emerged as relatively important predictors related to search variation for treatment (and SSI payments related to search variation for therapy too). Although public health funding is not uniquely dedicated to youth with ADHD, children and low-resource communities are among subpopulations most impacted (Trust for America’s Health, 2019). Chronic underfunding (Trust for America’s Health, 2019) and budget cuts (Hoagwood et al., 2018) disrupt research and program capacity to address public health crises. Possibly, when food and safety are immediate concerns, families may have limited bandwidth to see a mental health professional, motivating quick and free Google searches instead. Additionally, geographical variation in SSI receipt and special education enrollments (Schmidt & Sevak, 2017) may explain the connection between SSI payments and interest in therapy. Resources allocated for low-income families, such as those receiving SSI, may encourage online searches pertaining to psychological services.

Special care needs emerged as an important predictor for search variation for ADHD and ADHD medication. Our results may reflect overlapping criteria for special health care needs in 2018 NSCH and ADHD. In the NSCH, youth who have special health care needs experienced consequences due to a health condition that lasts >12 months. Similarly, diagnosing ADHD (a chronic condition) requires assessing for impairments. In 2016-2017 NSCH, one third of youth with special health care needs had ADHD (Abdi et al., 2020). Possibly, a large subgroup of those families searched for medication-related information.

The connection between information seeking and service utilization may result from a lack of knowledge and/or resources. Teachers are among the first professionals parents consult about ADHD-related questions (Sayal et al., 2006), vital in referrals, assessment and treatment (Pelham, Jr. et al., 2005). However, teachers often lack science-informed knowledge about ADHD (Akram et al., 2009; Poznanski et al., 2021). Plus, many youth received ADHD diagnoses and medication prescriptions during pediatric visits (McDonald & Jalbert, 2013), most of which last <16 minutes (https://www.statista.com/statistics/697310/pediatricians-minutes-with-patients-us/)and might motivate searching for unanswered questions. On the other hand, online information may motivate conversations (with teachers and/or providers), evaluation and treatment.

Limitations and Future Directions

Similar to many other studies using Google Trends (Arora et al., 2019; Mavragani et al., 2018), we extracted cross-sectional data for 2018 and could not draw causal inferences. Online information-seeking trends fluctuated with media and advocacy events (Zhao et al., under review). Whether our study can be replicated given the Covid-19 pandemic, and over time in general, needs further investigation. Families of adolescents with ADHD experienced more challenges of daily routines and parent-teacher communication during remote learning (Becker et al., 2020), suggesting a potentially higher level of need for online information to address ADHD-related concerns.

Not all individuals *know* and *use* our search terms, although most parents in a school district sample reported having heard of ADHD (Bussing et al., 2012). We included "ADHD" in search terms to explore patterns specific to the disorder; however, this approach may disproportionally exclude families with low psychological literacy and minoritized ethnocultural backgrounds. For instance, Spanish-speaking families who may have searched "TDAH" (el *déficit de atención e hiperactividad*) would have been excluded. We seek to understand culturally relevant information-seeking patterns and disseminate information in families' preferred languages.

Our relatively large MAEs suggested possible instability of models. Although we used leave-one-out cross-validation, the lack of training-and-testing procedures can lead to overfitting and inflated associations (Hastie et al., 2009). However, given our aim was variable selection and our sample reflected population (50 states and DC), predictors identified by two different algorithms provide insight into relative importance of sociodemographic, clinical, funding, and policy factors. With more studies revealing predictors for state variation in service utilization and release of more datasets, models may yield better performance with additional theory-informed predictors.

Future analyses could benefit from smaller spatial units, because variations in ADHD diagnoses and treatment are even larger at the practice and county levels (Mayne et al., 2016; McDonald & Jalbert, 2013; Moscone & Knapp, 2005; Schmidt & Sevak, 2017). For instance, spatial analyses revealed mental health expenditures are clustered in metropolitan areas (Moscone & Knapp, 2005). Proximity to research clinics may increase access to science-informed care, which also may be captured at practice and county levels.

Conclusion

Survey studies of ADHD-related information-seeking behaviors and preferences are informative yet restricted to subpopulations close to research institutions (Bussing et al., 2007, 2012). We found information-seeking patterns varied across states and by search terms. Moreover, patterns of diagnoses, treatment and medication use, as well as sociodemographic and funding were important factors to explain state variation in search interest. Google Trends, free and naturalistic, may detect large gaps in need for, access to, and utilization of information and care. If search engine is a reliable screener for systematic resource deprivation, we may develop predictive models for resource allocation and more effectively reach underserved communities with equitable information and care.

Tables and Figures

Table 1. *Bivariate Correlation of Variables Examining Information Seeking, Diagnoses and Treatment.*

	Diagnoses, All (%)	Diagnoses, Mild (%)	Diagnoses, Moderate/Severe (%)	Currently taking medications for ADHD (%)	Currently having ADHD and receiving behavior therapy (%)
"ADHD"	.35***	.19*	.33***	.35***	.33***
"ADHD treatment"	.18	.22*	.12	.27**	.32**
"ADHD medication"	.41***	.23*	.39***	.48***	.20*
"ADHD therapy"	.01	.07	-.05	.03	.03

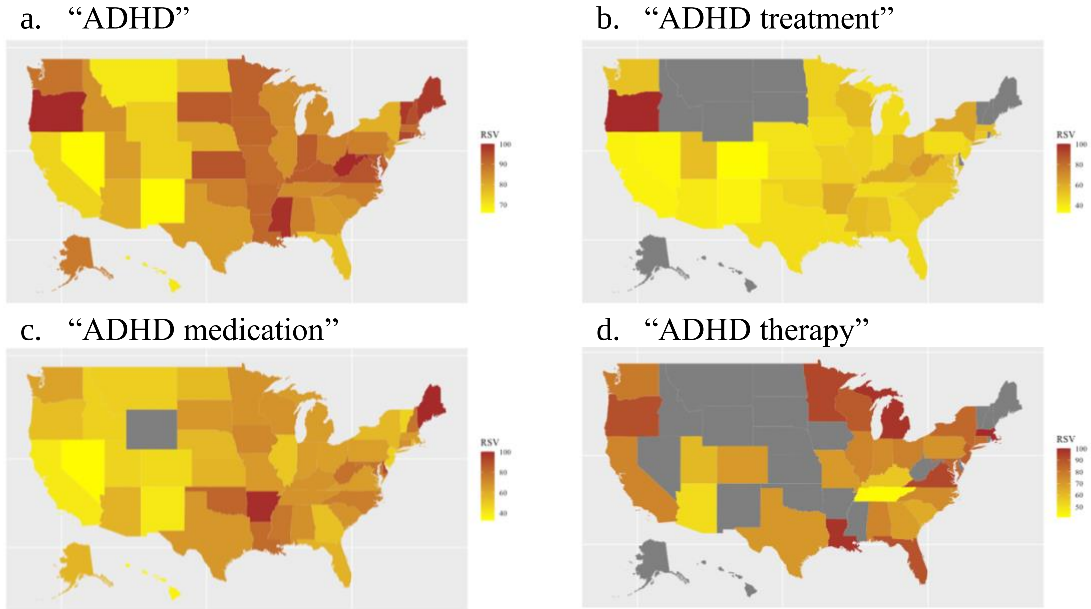
Note. State-level relative search volumes using "ADHD," "ADHD treatment," "ADHD medication," and "ADHD therapy" were extracted from Google Trends for online information-seeking patterns. ADHD = attention-deficit/hyperactivity disorder. *** $p<.001$, ** $p<.01$, * $p<.05$.

Table 2. *Coefficients in Final Elastic Net Models for State-level Google Trends Relative Search Volumes.*

	ADHD	ADHD treatment	ADHD medication	ADHD therapy
Intercept	184.71	48.38	49.43	-108.74
Current ADHD diagnoses, all (%)	4.71*	-	-	-
Current ADHD diagnoses, rated mild (%)	-5.68	-	-	-
Current ADHD diagnoses, rated moderate/severe (%)	-6.35*	-	1.39	-
Current ADHD treatment, medication (%)	0.86	-	0.44*	-
Current ADHD treatment, psychosocial (%)	1.69	-	-	-
Children with special care needs (%)	3.54*	-	1.86*	-
Parent-reported unmet need (%)	-0.21	-	0.07	-
1 or more preventive visit (%)	-0.49	-	-	-
Avoided care due to cost (%)	-0.17	-	-0.01	-
Children living in poverty (%)	-356.75		-0.01	-
Median income ($)	> -.01	-	-	-
Per capita income ($)	< 0.01	-	-	< 0.01
Youth residing with > 1 unemployed parent (%)	435.04	-	-67.46	-
Unemployment rate (%)	3.25	-	-	-
Uninsured population (%)	167.75	-	-	-
Uninsured youth (%)	-0.41	-	-	-
Youth, private insurance only (%)	-1.07	-	-	-
American Indian, Alaskan Native or Native Hawaii (%)	-146.41	-	38.13	-
Non-Hispanic Asian (%)	72.84	-	-	19.59
Non-Hispanic Black (%)	-50.52	-	-	13.03
Non-Hispanic Multiracial (%)	-40.07	-	-	-
Non-Hispanic White (%)	9.19*	-	-	-
Hispanic Or Latinx (%)	-11.49*	-	-32.42	-
Elementary school entry age (years)	-3.46	-	-2.92	-
Medicaid/CHIP apps can be submitted by phone (Y/N)	1.18	-	-7.9	-
Medicaid/CHIP online application can be submitted on mobile devices (Y/N)	-2.38	-	-	-
Medicaid/CHIP website mobile-friendly design (Y/N)	-8.41	-	4.14	-
Medicaid/CHIP mobile app available (Y/N)	-9.24	-	-	-
Medicaid eligibility, minimum income ($)	10.85	-	-	-
Public assistance (%)	2.02	-	-	-
Public health funding ($)	> -0.01	-0.02*	-	> -0.01
SSI beneficiaries in population	-218.01	-	-	-
SSI payments per recipient ($)	< 0.01	< 0.01*	< 0.01	< 0.01*
Mental health providers per 100,000 population	< 0.01	-	-	-
Primary care physicians per 10,000 population	-0.14	-	-	-
Pediatricians per 10,000 children, age 70 and under	0.02	-	-	-
Active physicians, age 39 or younger (%)	56.58	-	-	-
Active physicians, age 60 or older (%)	78.09	-	-	-
K-12 mandatory computer science education (Y/N)	-1.13	-	-	-
Access to broadband internet at home (%)	-1.49	-	-	1.62

Note. *The variable was selected by both of the elastic net and random forest models. SSI = supplemental security income. CHIP=Children's Health Insurance Program. ADHD = attention-deficit/hyperactivity disorder.

Figure 1. *State Variations in Google Trends Relative Search Volumes*

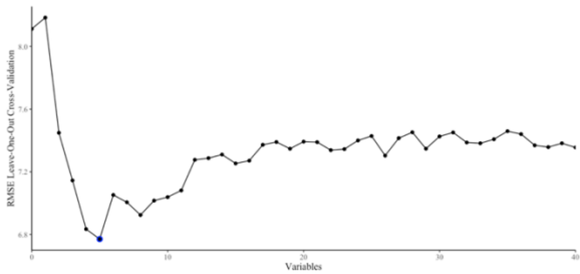


Note. Grey areas represented missing data when we extracted data from Google Trends. Missing data represented relative search volumes very close to zero and thus were coded as zeroes for analyses in the current study. ADHD=attention-deficit/hyperactivity disorder.

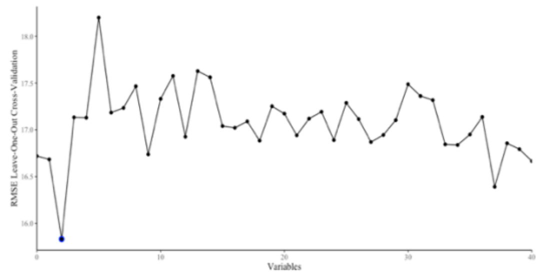
Figure 2.

Changes in Root Mean Square Error (RMSE) by Number of Selected Variables in Random Forest

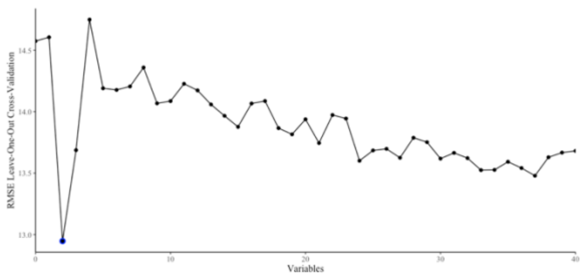
a. "ADHD"



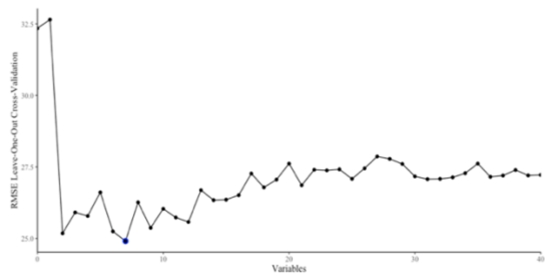
b. "ADHD treatment"



c. "ADHD medication"



d. "ADHD therapy"



Note. ADHD = attention-deficit/hyperactivity disorder.

IV. UNPACKING INEQUITIES IN ADHD DIAGNOSIS: EXAMINING INDIVIDUAL LEVEL RACE/ETHNICITY AND STATE-LEVEL ONLINE INFORMATION-SEEKING PATTERNS

This manuscript will be submitted to Clinical Psychological Science; thus, it adheres to the use of APA 7th Edition formatting guidelines.

Zhao, X., Hayes, T., & Frazier, S. L. (in preparation). Unpacking Inequities in ADHD Diagnosis: Examining Individual-level Race/Ethnicity and State-level Online Information-Seeking Patterns

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Abstract

Objective. Attention-deficit/hyperactivity disorder (ADHD) is a prevalent, persistent, and costly mental health condition. The internet is an increasingly popular source for information related to ADHD. With a nationally representative sample (2018 NSCH), we aim to separate individual- and state-level effects to examine inequities in ADHD diagnoses. *Method.* We extracted state-level relative search volumes using "ADHD" from Google Trends and sociodemographic and clinical variables from the 2018 National Survey of Children's Health. With a large (N=26,835) and nationally representative sample, we applied multilevel modeling to examine the roles of 1) individual-level race/ethnicity, 2) state-level information-seeking patterns, and 3) the association of their interaction to ADHD diagnoses. *Results.* Individual-level racial/ethnic background and state-level information-seeking patterns partially predicted ADHD diagnoses; however, their cross-level interaction did not. *Conclusion.* This study adds to the strong body of evidence documenting racial/ethnic inequities in mental health care and the growing literature on the impact of the digital divide on population health, indicating an urgent need for addressing inequities in mental health care. Increasing public interest in and access to empirically supported online information may increase access to care, especially among people of color.

***Keywords*:** Racial Disparities, ADHD, Google Trends, Latinx

Literature Review

Attention-deficit/hyperactivity disorder (ADHD) is a persistent, costly and prevalent neurodevelopmental disorder, more commonly diagnosed in males (Barkley, 2018). ADHD is characterized by core symptoms of inattention, hyperactivity, and impulsivity and cross-setting (and often long-term) functional impairments (Barkley, 2018; Gordon & Fabiano, 2019; Kuriyan et al., 2013; Pelham et al., 2020). ADHD and its associated impairments incur substantial global burden, with national estimates ranging from 12 million to 141 billion U.S. dollars (Chhibber et al., 2021; Doshi et al., 2012). Documenting the true prevalence of ADHD remains challenging in light of problems of overdiagnosis (e.g., following quick screening rather than full evaluation incorporating multi-informant and multi-method data given limited resources) and underdiagnosis (e.g., reflecting systemic inequities in healthcare and education systems).

State-level diagnostic prevalence of ADHD varies largely (Danielson et al., 2018; Fulton et al., 2015; Visser et al., 2014). Nevertheless, national surveys report that youth of color were less likely to receive an ADHD diagnosis compared to White youth across the developmental span (Coker et al., 2016; Danielson et al., 2018; Morgan et al., 2013). Additionally, a recent systematic review reveals that youth from disadvantaged socioeconomic backgrounds are at higher risk for social and behavioral outcomes (Peverill et al., 2021). Inequities in diagnoses have been attributed in part to income, insurance status, socio-cultural norms, stigma, psychological literacy, expectations, attitudes, funding, and policy that influence service-seeking for youth (Fulton et al., 2009, 2015; Reardon et al., 2017). The high cost of illness and persistent inequities highlight the need for understanding and improving access to information and care for ethnoculturally diverse samples.

Given the increasing accessibility of the internet in the U.S. (https://www.statista.com/statistics/590800/internet-usage-reach-usa/), more than 80% of adults search for health information online (Jacobs et al., 2017). Access and utilization of online health information are partly associated with patients' and/or caregivers' emotional status (e.g., elevated health anxiety; Brown et al., 2020), decisions (e.g., deciding to visit a professional; Yu et al., 2019), behaviors (e.g., more frequent physician visits; Brown et al., 2020), preferences (e.g., for patient-centered care; Baldwin et al., 2008), and perceptions (e.g., sense of control, empowerment, confident in treatment settings and quality of patient-provider relationships; Tan & Goonawardene, 2017). For example, in a hospital waiting room in Canada, 80% of caregivers (n=143) reported starting with a public search engine (e.g., Google) when seeking health-related information for their child (Pehora et al., 2015), highlighting the importance and opportunity of online information to influence evaluation- and treatment-seeking patterns among families.

The impact of online health information-seeking behaviors on ADHD diagnosis merits additional study because of 1) the increasing popularity of using the internet as a source for ADHD-specific information among parents (Bussing et al., 2012; Sage et al., 2018), youth (Bussing et al., 2012) and teachers (Akram et al., 2009), 2) the strong evidence for a collaborative care model, as parents, schools, youth, general practitioners, and specialists are vital to assessment and treatment (French et al., 2019; Pelham, Jr. et al., 2005; Pfiffner et al., 2018), and 3) online health information may be particularly important to recognizing problems, characterized by racial/ethnic differences in perceived need for care (Gerdes et al., 2014; Haack et al., 2018), and is often the first step of seeking professional help (Eiraldi et al., 2006). Recently, Zhao and colleagues (under review) reported cross-sectional correlates between information-seeking patterns and diagnostic prevalence at the state level, utilizing population surveys and search engine data. The impact of information-seeking patterns at the state level on *individual* ADHD diagnoses, however, has not been tested empirically among families of youth.

Information inequities may contribute to sociodemographic differences in diagnoses. In a large school district sample, Black families were less likely to seek ADHD-related information online compared to White families, corresponding to lower levels of ADHD awareness and knowledge (Bussing et al., 2012). Information-seeking behaviors and ADHD knowledge may impact the four stages of help-seeking as described by Eiraldi and colleagues (2006): problem recognition, decision to seek help, service selection, service utilization. Despite the reported racial/ethnic differences in information sources (Bussing et al., 2012) and help-seeking pathways (Eiraldi et al., 2006), most studies of parents' online information-seeking behaviors rely on clinical samples with a large percentage of White families (Kubb & Foran, 2020; Sage et al., 2018) and presume families have equal opportunities for participating in the research study. Families who have limited access to mental health information and reside far from the research institutions may be largely underrepresented in this line of research.

Emerging studies in the last decade have incorporated online forum and/or search engine data to examine the content and impact of online information-seeking behaviors related to ADHD (Rosenblum & Yom-Tov, 2017; Terbeck & Chesterman, 2012). More recently, machine learning analyses revealed that percentage of Hispanic/Latinx youth at the state level was a relatively important predictor to explain variations in searching Google for “ADHD” at the state level, documenting the intersection between race/ethnicity and online information-seeking patterns (Zhao et al., under review). Such findings highlight possible information inequities among underserved communities. Although these studies extended analyses beyond local samples residing close to research institutions to population-level findings across states and regions, they provide limited information relating population-level findings to individual-level diagnostic and sociodemographic information.

To summarize, we know that racial/ethnic inequities are consistently documented for ADHD diagnoses (Danielson et al., 2018; Morgan et al., 2013) and that the internet is an increasingly popular source for health information in general, and ADHD-related information specifically (Akram et al., 2009; Bussing et al., 2012; Kubb & Foran, 2020; Sage et al., 2018; Terbeck & Chesterman, 2012). It is not clear to what extent *state-level* online information-seeking patterns (i.e., differences in relative search interest in ADHD) impact *individual-level* ADHD diagnoses among youth. In this study, we utilized a multilevel framework to examine three main hypotheses: 1) youth of color will be less likely to receive ADHD diagnoses than White youth (White>Black>Latinx>Asian), 2) state-level online information seeking related to ADHD will predict ADHD diagnoses, and 3) there will be a cross-level interaction between individual-level race/ethnicity and state-level online information-seeking patterns, such that youth of color will be even less likely to receive an ADHD diagnosis when residing in a state with less relative search interest in ADHD.

Method

Data Source and Sample

We extracted data from the 2018 National Survey of Children's Health (NSCH; Child and Adolescent Health Measurement Initiative [CAHMI], 2019). The study did not require Institutional Review Board approval or collection of informed consent, as data are publicly available. The corresponding author completed the data use agreement from the Data Resource Center and CAHMI. A national representative sample of caregivers of youth aged 0 to 17 years completed questionnaires via mailed packets and online surveys to provide demographic and health information; one child was randomly selected in families with multiple children. Details of the survey instruments are available at https://www.childhealthdata.org/learn-about-the-nsch/survey-instruments.

In the current study, data were based on survey responses from 26,205 caregivers of youth aged 3 to 17 years old, who provided a valid response to the status of ADHD diagnosis. Demographic characteristics by these three conditions are presented in Table 1. The number of respondents averaged 513 per U.S. state and Washington D.C., ranging from 396 in D.C. to 672 in Arkansas. Individual responses (level 1) were nested in their states of residency (50 U.S. states and Washington D.C.; level 2).

Variables

Level-1 predictors. Race/ethnicity was the main variable of interest. We controlled for income, highest education in the household, child's sex and child's age in years.

Level-2 predictor. We extracted Google Trends Relative Search Volumes (RSV) at the state level (https://trends.google.com/trends/?geo=US). State-level RSVs are commonly used in the medical field as a metric to reflect geographical variation in public interest and information-seeking behaviors online (Arora et al., 2019; Mavragani et al., 2018).

We extracted state-level RSVs for "ADHD" in 2018 from Google Trends. State-level RSVs were standardized and scaled prior to data extraction. A proportion was first calculated by dividing the number of searches containing "ADHD" by the number of all searches within each state and then scaling relevant to all other states. State-level RSVs range from 0 to 100; the state with highest search interest out of all 50 states and D.C. has an RSV=100.

Dependent variable. The dependent variable was *current* ADHD diagnosis (1 = Yes, 0 = No). Caregivers were asked, "Has a doctor or other health care provider EVER told you that this child has Attention Deficit Disorder or Attention Deficit/Hyperactivity Disorder, that is, ADD or ADHD?" Caregivers who responded yes to this initial question were asked, "Does this child CURRENTLY have the condition?" In the current study, children without current ADHD diagnoses included those who had never been diagnosed with ADHD (n=23,295) and those who were ever diagnosed but do not currently have a diagnosis of ADHD (n=233).

Analytical Plan

We completed all data extraction and analyses using R (version 4.0.3). Applying hierarchical multilevel modeling (MLM) regression models, we assessed the fit of each step after controlling for initial (earlier) steps of variables. MLM allows for modeling between-state variation and partitioning level-1 (individual-level) and level-2 (state-level) effects. All categorical variables were dummy coded. All level-1 predictors (including continuous and dummy coded categorical variables) were cluster-mean centered (Enders & Tofighi, 2007). We present level-specific descriptive statistics in Appendix 1. The order of entry of sets of independent variables into the regression model was predetermined to test for aforementioned hypotheses.

Our first model was a random intercept model with current ADHD diagnosis as the binary criterion variable and all level-1 predictor variables (i.e., household income, highest education in the household, child sex, child age, and child race/ethnicity). Our second model included all variables in Model 1 and online search interest (Google RSV) as the level-2 predictor. Our third model added cross-level interactions between race/ethnicity and state-level search interest to the second model. For model comparison, we computed Akaike information criterion (AIC; Akaike, 1974) and Bayesian information criterion (BIC) and conducted X^2 tests to compare models.

Results

Intraclass Correlation and Model Selection

We computed intraclass correlation coefficients[1], using maximum likelihood estimation. The intraclass correlation (ICC) was .01, indicating that residency of state accounted for 1% of the variance in ADHD diagnosis. Research has shown that we can benefit from analyses in the MLM framework when ICC≥.01 (Bliese, 1998). Model comparison is presented in Table 2. Model 2 (AIC=16,322, BIC=16,543) fit data significantly better than Model 1 (AIC=16,336, BIC=16,548), X^2=15.58, df=1, p<.001). Model 3, which added the cross-level interaction to Model 2, did not outperform Model

[1] In line with recommendations from the methodological literature, for our binary logistic outcome, we set the within-level residual variance equal to $\pi^2/3$, the variance of a standard logistic distribution when calculating the ICC.

2, *AIC*=16,331, *BIC*=16,617, X^2=7.22, *df*=8, *p*=.513. Thus, Model 2 (including all level-1 predictors and state-level search interest) was selected as the final model. Parameters of all three models are presented in Table 3.

Hypothesis 1: Youth of Color Will Be Less Likely to Receive ADHD Diagnoses (White>Black>Latinx>Asian)

As shown in Table 2, in Model 2 (best-fitting model), youth of color were less likely to receive an ADHD diagnosis. Within states (at level 1), Black (*b*=-0.24, *OR*=0.78, *SE*=0.09, *z*=-2.80, *p*=.005), Latinx/Hispanic (*b*=-0.39, *OR*=0.68, *SE*=0.08, *z*=-5.08, *p*<.001), and Asian (*b*=-1.30, *OR*=0.27, *SE*=0.17, *z*=-7.65, *p*<.001) youth were less likely to have a current ADHD diagnosis, compared to White youth. Compared to White youth (most likely to receive an ADHD diagnosis), Black youth were 22% less likely, Latinx youth were 32% less likely and Asian youth were 73% less likely to receive an ADHD diagnosis, after we controlled for other variables in the model.

Hypothesis 2: State-level Online Information Seeking Related to ADHD Will Predict Diagnoses.

As shown in Table 2, in Model 2 (best-fitting model), state-level search interest positively and significantly predicted ADHD diagnoses, *b*=0.01, *OR*=1.01, *SE*=0.00, *z*=3.97, *p*< .001. We computed Rights and Sterba's suite of multilevel R^2 (Rights & Sterba, 2019a, 2019b) and found the fixed effect (between-level) level-2 variable predicted a 1% of the total variance, which is almost all of the between-state variance.

Hypothesis 3: There Will be a Cross-Level Interaction Between Individual-Level Race/Ethnicity and State-Level Online Information-Seeking Patterns.

Contrary to our predictions, there was no significant interaction between individual-level (level-1) race/ethnicity and state-level (level-2) search interest in Model 3 (Table 2). These results were consistent with model comparison results where Model 2 was demonstrated as the best-fitting model to the data (Table 3). Youth were not less likely to receive an ADHD diagnosis when residing in a state with less relative search interest in ADHD.

Covariates: Income, Education in the Household, Child's Sex and Child's Age

At level 1, youth living in high poverty (0-99% FPL: b=0.40, OR=1.49, SE=0.07, z=5.54, p<.001; 100-199% FPL: b=0.17, OR=1.19, SE=0.07, z=2.63, p=.008) were more likely to have an ADHD diagnosis. Older youth also were more likely to have a current ADHD diagnosis, b=0.01, OR=1.1, SE=0.01, z=18.90, p<.001. Compared to male youth, female youth were less likely to have a current ADHD diagnosis, b=-0.78, OR=0.46, SE=0.04, z=-17.68, p<.001. Highest education in household below college (high school or GED: b=0.23, OR=1.26, SE=0.06, z=3.54, p<.001; some college or technical school: b=0.30, OR=1.35, SE=0.05, z=5.81, p<.001) was, mostly, associated with higher likelihood of ADHD diagnosis for children; however, this association was not reported for families with "Less than high school" education at level 1. Instead, youth were more likely to receive an ADHD diagnosis in states where there were higher percentage of households with less than high school education (level-2 specific effect), b=6.95, SE=2.63, z=2.64, p=.008.

Discussion

This study adds to the strong body of evidence documenting racial/ethnic inequities in mental health care and the growing literature on the impact of the digital divide on population health. With a large (N=26,835) and nationally representative sample (2018 NSCH), we separated individual- and state-level effects to examine inequities in ADHD diagnoses. Specifically, we applied multilevel modeling to examine the extent to which *individual-level* racial/ethnic backgrounds and *state-level* information-seeking variations relate to ADHD diagnosis, after controlling for poverty status, highest education in household, child's sex, and child's age. Our hypotheses were partially supported. Results support a large body of data pointing to sociodemographic inequality in ADHD diagnoses and highlight the important role of online information-seeking. The absence of an interaction between the two suggests the need for level-specific investigation.

Youth of Color Were Less Likely to Have a Current ADHD Diagnosis

Findings revealed that youth of color were less likely to receive an ADHD diagnosis, supporting hypothesis 1. This result is consistent with national surveys reporting racial/ethnic differences in ADHD prevalence (Coker et al., 2016; Danielson et al., 2018; Morgan et al., 2013) and prior work that underscores sociodemographic facilitators and barriers of help-seeking pathways for ethnoculturally minoritized families (Cauce et al., 2002; Eiraldi et al., 2006). Given our focus on ADHD diagnosis rather than service utilization in general, findings apply in particular to the initial problem recognition stage (Gerdes et al., 2014; Haack et al., 2018), which is often the first step toward seeking professional help (Eiraldi et al., 2006). Note Danielson et al. (2018)

reported Black youth were more likely to receive an ADHD diagnosis (ever and current), compared to White youth, in the 2016 NSCH (reverse of what we found here in the 2018 NSCH). Perhaps this inconsistency resulted from differences in analytical procedures (e.g., model specification and covariates). Alternatively, this finding may be considered in context of policy changes corresponding to years of data collection; notably, efforts to dismantle the Affordable Care Act that began in 2016 reversed improvements in insurance coverage for youth and mitigation in racial/ethnic disparities (Ortega et al., 2020).

Findings on covariates are consistent with prior literature. Males and older youth were more likely to have a current ADHD diagnosis, consistent with results from the 2016 NSCH (Danielson et al., 2018). Youth living in high poverty (family income<200% federal poverty line) and in households with lower educational attainment (i.e., parents received high school diploma or GED; some college or technical school) were more likely to receive an ADHD diagnosis. Such results can be interpreted in the context of four lines of literature: 1) systematic inequities for access to information and diagnoses; 2) youth experiencing financial hardship and from disadvantaged socioeconomic backgrounds may be at higher risk for behavioral problems and socioemotional impairments (Peverill et al., 2021); 3) caregivers of youth with ADHD experience high economic burden, such as loss of work productivity and employment, which leads to lower income (Zhao et al., 2019), and 4) ADHD is chronic and heritable, associated with long-term educational and occupational impairments (Gordon & Fabiano, 2019; Kuriyan et al., 2013). Notably, residing in a household with less than high school education did not relate to a child's ADHD diagnosis at the individual level (recall level-1 analyses); this may reflect small and uneven sample sizes across states under this category.

State-Level Online Information Seeking Predicted Individual Diagnosis

State-level search interest in ADHD positively predicted ADHD diagnoses, after controlling for level-1 predictors (i.e., race/ethnicity, poverty status, highest education in household, child's sex, and child's age), supporting hypothesis 2. Note the relatively low OR = 1.01 may result from 1) the small sample size at level 2 (n = 50 U.S. and Washington D.C.) and 2) relatively low variability of data at level 2 (ICC = .01). Despite the small OR, online search interest explained almost all of the variance at level 2. Thus, these findings highlight the important association of information-seeking online and ADHD diagnosis, above and beyond sociodemographic inequities. This result extends prior evidence of positive correlates between ADHD search interest and diagnostic prevalence at the state level (Zhao et al., under review). Although Google searching for "ADHD" is not exclusively applicable to youth-serving settings, we found significant association between state-level search interest and parent-reported current ADHD diagnosis for their child in the NCHS. This result is consistent with prior studies reporting the internet has become an increasingly popular source for ADHD-related information among youth, parents and teachers (Akram et al., 2009; Bussing et al., 2012; Sage et al., 2018) and most service-seeking parents start with public search engines (Pehora et al., 2015).

No Interaction Between Race/Ethnicity and Information-Seeking.

There was no interaction between individual-level racial/ethnic background and state-level information-seeking pattern, contrary to hypothesis 3. Specifically, the state-level online information-seeking variation did not affect the odds that youth of color would have a current ADHD diagnosis over and above other included characteristics. The variable (Google Trends RSVs) measuring information-seeking patterns is not available at the individual level (Arora et al., 2019; Mavragani et al., 2018); recall state-level RSVs are scaled values displaying *relative* interest in “ADHD” compared to all other states rather than the *absolute* search volumes of identifiable individuals. Thus, we were unable to examine temporal relations between information-seeking behaviors and sociocultural beliefs at the individual level, which may affect seeking and/or reporting an ADHD diagnosis.

Limitations and Future Research

First, despite the significant associations reported at individual and state levels, we note the nature of *association* rather than *causality* in the current study. Data are cross-sectional; thus, we cannot draw conclusions for specific individual processes and pathways, which is a common limitation for Google Trends data (Arora et al., 2019; Mavragani et al., 2018). Possibly, a multilevel mediation may be detected should longitudinal data (e.g., search behaviors of individual families over time) become available in the future. A close examination of parameter changes from Model 1 and Model 2 provided preliminary evidence for this hypothesis. There was a significant state-level effect of Latinx/Hispanic youth on having an ADHD diagnoses in Model 1, indicating residing in states with more Hispanic families reduce the likelihood of having an ADHD diagnosis. This association was not significant in Model 2 (when state-level search interest was added as a level-2 predictor), suggesting a potential mediation rather than moderation (what was tested in the current study).

Second, we did not include information about cultural identities beyond race and ethnicity – such as nation of origin, immigration status, acculturation (concordance/discordance within a family; acculturative stress), enculturation and language preference – due to concerns of collinearity. However, it is important to consider intersectionality (Hays, 2016), and especially to avoid monolithic conclusions about how simply identifying with a particular race or ethnicity may influence health information seeking and decision making. For example, not every family knows and uses the word "ADHD" during Google searches; Spanish-speaking families may search "TADH (Trastorno por Déficit de la Atención con Hiperactividad)." Thus, there may be a language-specific effect on information-seeking behaviors. Future research could benefit from exploring more culture-relevant variables as they relate to online information-seeking behaviors, ideally in large, ethnoculturally and linguistically diverse longitudinal samples.

Third, we are not able to draw conclusions specific to *evidence-based* information and care. Increasingly studies have demonstrated that quality of health information online varies, thus a layperson audience may experience challenges of evaluating the quality of online information, receiving and/or utilizing empirically unsupported information (Swire-Thompson & Lazer, 2020). Our variable for information-seeking patterns (state-level RSVs from Google Trends) was extracted for the search term "ADHD," which captured active information seeking online, possibly reflecting accessing and consuming *popular* (decided by Google's algorithms), but not necessarily high-quality, information on the internet.

Fourth, the NCHS did not ask caregivers to report the circumstances of their child's ADHD diagnosis, such as who gave the diagnosis (e.g., psychologist, psychiatrist, pediatrician) or on what information it was based (e.g., multi-informant and multi-method data, following evidence-based practice, or brief screening) (Pelham, Jr. et al., 2005). We suspect most may have followed quick screening because the majority of pediatric visits last less than 25 minutes (https://www.statista.com/statistics/697310/pediatricians-minutes-with-patients-us/). More research is needed to understand whether and how online-information seeking helps or hinders access to *science-informed* decision making and care, particularly for racially/ethnically minoritized subpopulations.

Fifth, our analyses were conducted for 2018, and thus may not generalize to diagnosis and information seeking during (or after) the Covid-19 global pandemic. Exacerbated ADHD symptoms and functional impairment experienced by youth with ADHD have been reported in early-pandemic survey studies (Becker et al., 2020; Breaux et al., 2021; Sibley et al., 2021), indicating high information need. Additionally, diminished teacher-parent communication and school-based support during remote learning (Breaux et al., 2021) suggests limited opportunities for gathering information from teachers and schools (and thus a potentially higher need for related information online). Given these changes in information need and access, the internet may have become even more popular and important for ADHD-related information for families. Hence, there will be substantial need for understanding the relations between online information-seeking behaviors and mental health care since 2020, especially among underserved subpopulations (e.g., those with limited digital skills and psychological literacy). Thus, we hypothesize that future studies may find an even stronger association between online information-seeking behaviors and ADHD diagnosis.

Conclusion

Persistent racial/ethnic inequities warrant systematic changes in policy and clinical care that can attend to the needs of underserved communities. The digital divide adds complexity to persistent racial/ethnic and socioeconomic inequities in ADHD diagnosis. These findings highlight that equitable online information may increase access to mental health diagnoses and in turn, resources and services. Future research is needed for understanding individual pathways and the extent to which online information inspires seeking *evidence-based* care. There is potential to leverage public search engine data to enhance access to empirically-supported mental health information and care.

Tables

Table 1. *Sociodemographic Information by ADHD Diagnostic Condition.*

	Does not have ADHD (n = 23,925)		Ever told, but does not currently have ADHD (n = 233)		Currently has ADHD (n = 2,677)			
	M or *n*	*SD* or *%*	*M* or *n*	*SD* or *%*	*M* or *n*	*SD* or *%*	X^2 *(df)*	*p*
Race/Ethnicity							105.32 (8)	< .001
Latinx, Hispanic	2,815	12%	25	11%	248	9%		
White, non-Hispanic	15,998	67%	165	71%	1,981	74%		
Black, non-Hispanic	1,491	6%	19	8%	1,93	7%		
Asian, non-Hispanic	1,209	5%	5	2%	38	1%		
Others	1,782	7%	19	8%	217	8%		
Poverty Status							59.61(6)	< .001
0-99% FPL	2,641	11%	30	13%	415	16%		
100-199% FPL	3,749	16%	48	21%	483	18%		
200-399% FPL	7,177	30%	72	31%	783	29%		
400% FPL or more	9,728	41%	83	36%	996	37%		
Highest education in the household							96.97 (6)	< .001
Less than high school	633	3%	7	3%	67	3%		
High school/GED	3,097	13%	41	18%	448	17%		
Some college/technical school	5,485	23%	67	29%	788	29%		
College and above	14,080	59%	118	51%	1,374	51%		
Child sex: Male	11,699	49%	159	68%	1,845	69%	360.51 (2)	< .001
Child age	10.48yr	4.48yr	14.07yr	2.97yr	12.24yr	3.38yr		

Note. FPL = federal poverty level. RSV = relative search volume

Table 2. *Descriptive Statistics by Level*

	M	*SD*
	Level 1 (individual-level, within-cluster)	
Race: Reference group = White, non-Hispanic		
Latinx, Hispanic	0	0.31
Black, non-Hispanic	0	0.24
Asian, non-Hispanic	0	0.21
Other/Multi-racial, non-Hispanic	0	0.26
Income: Reference = 400% FPL or more		
0-99% FPL	0	0.32
100-199% FPL	0	0.37
200-399% FPL	0	0.46
Highest education in the household: reference level = college and above		
Less than high school	0	0.16
High school or GED	0	0.34
Some college or technical school	0	0.43
Child sex: Reference group = Male	0	0.02
Child age	0	0.50
	Level 2 (state-level/between-cluster)	
Race: Reference group = White, non-Hispanic		
Hispanic, non-Hispanic	0.12	0.10
Black, non-Hispanic	0.06	0.07
Asian, non-Hispanic	0.05	0.05
Other/Multi-racial, non-Hispanic	0.08	0.05
Income: reference = 400% FPL or more		
0-99% FPL	0.12	0.04
100-199% FPL	0.16	0.03
200-399% FPL	0.31	0.06
Highest education in the household: Reference level = college and above		
Less than high school	0.03	0.01
High school or GED	0.14	0.04
Some college or technical school	0.24	0.04
Child sex: Reference group = Male	0.48	0.02
Child age	0.22	0.02

Note. Level-1 means = means of cluster-mean-centered scores. Level-2 means = cluster means. Clusters = states. FPL = federal poverty level. RSV = relative search volume.

Table 3. *Model Comparison.*

	AIC	*BIC*	*logLik*	*deviance*	X^2	*df*	*p*
Model 1	16,336	16,548	-8141.8	16284	--	--	--
Model 2	16,322	16,543	-8134.0	16268	15.58	1	< .001
Model 3	16,331	16,617	-8130.4	16261	7.22	8	0.513

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion.

Table 4. *Results of Multi-level Modeling Predicting Current ADHD diagnoses*

	Model 1: Random intercept with level-1 predictors					Model 2: Model 1 + RSV as a level-2 predictor					Model 3: Model 2 + cross-level interaction				
	Fixed Effects					Fixed Effects					Fixed Effects				
	Coef	*OR*	*SE*	*z*	*p*	*Coef*	*OR*	*SE*	*z*	*p*	*Coef*	*OR*	*SE*	*z*	*p*
Intercept	-2.85	0.06	1.34	-2.13	.034	-2.59	0.08	1.29	-2.00	.045	-3.46	0.03	1.43	-2.42	.016
	Within states					Within states					Within states				
Race: reference group = White, non-Hispanic															
Latinx, Hispanic	-0.39	0.68	0.08	-5.08	< .001	-0.39	0.68	0.08	-5.08	< .001	-1.16	0.32	0.70	-1.64	.101
Black, non-Hispanic	-0.24	0.78	0.09	-2.80	.005	-0.24	0.78	0.09	-2.78	.005	0.09	1.09	1.12	0.08	.937
Asian, non-Hispanic	-1.30	0.27	0.17	-7.65	< .001	-1.30	0.27	0.17	-7.64	< .001	0.53	1.69	1.53	0.34	.731
Other/Multi-racial, non-Hispanic	0.00	1.00	0.08	-0.01	.996	0.00	1.00	0.08	0.01	.992	-0.40	0.67	0.79	-0.51	.609
Income: reference = 400% FPL or more															
0-99% FPL	0.40	1.49	0.07	5.54	< .001	0.40	1.49	0.07	5.54	< .001	0.40	1.49	0.07	5.51	<.001
100-199% FPL	0.17	1.19	0.07	2.62	.009	0.17	1.19	0.07	2.63	.008	0.17	1.19	0.07	2.61	.009
200-399% FPL	0.03	1.03	0.05	0.64	.520	0.04	1.04	0.05	0.66	.508	0.03	1.04	0.05	0.65	.513
Highest education in the household: reference level = college and above															
Less than high school	-0.05	0.95	0.14	-0.38	.705	-0.05	0.95	0.14	-0.37	.708	-0.05	0.95	0.14	-0.36	.722
High school or GED	0.23	1.26	0.06	3.55	< .001	0.23	1.26	0.06	3.54	< .001	0.23	1.26	0.06	3.54	< .001
Some college or technical school	0.30	1.35	0.05	5.83	< .001	0.30	1.35	0.05	5.81	< .001	0.30	1.35	0.05	5.84	< .001
Child sex: Reference group = Male	-0.78	0.46	0.04	-17.67	< .001	-0.78	0.46	0.04	-17.68	< .001	-0.78	0.46	0.04	-17.68	< .001
Child age	0.10	1.10	0.01	18.90	< .001	0.10	1.10	0.01	18.90	< .001	0.10	1.10	0.01	18.89	< .001
Latinx, Hispanic*RSV	-	-	-	-	-	-	-	-	-	-	0.01	1.01	0.01	1.10	.271
Black, non-Hispanic*RSV	-	-	-	-	-	-	-	-	-	-	0.00	1.00	0.01	-0.30	.766
Asian, non-Hispanic*RSV	-	-	-	-	-	-	-	-	-	-	-0.02	0.98	0.02	-1.20	.230
Other/Multi-racial, non-Hispanic*RSV	-	-	-	-	-	-	-	-	-	-	0.00	1.00	0.01	0.52	.604
	Between states					Between states					Between states				
Race: reference group = White, non-Hispanic															
Latinx, Hispanic	-1.19	0.31	0.42	-2.80	.005	-0.73	0.48	0.43	-1.72	.086	-2.93	0.05	2.69	-1.09	.277
Black, non-Hispanic	1.06	2.88	0.55	1.93	.054	0.81	2.24	0.52	1.54	.124	4.20	66.56	4.27	0.98	.326
Asian, non-Hispanic	-1.09	0.34	0.72	-1.51	.130	-0.65	0.52	0.70	-0.92	.356	-13.85	0.00	8.77	-1.58	.114
Other/Multi-racial, non-Hispanic	-0.19	0.83	0.64	-0.29	.771	-0.02	0.98	0.62	-0.04	.970	11.89	146376.58	8.29	1.43	.151
Income: reference = 400% FPL or more															
0-99% FPL	-0.34	0.71	1.32	-0.26	.796	0.72	2.06	1.30	0.56	.578	1.63	5.10	1.46	1.12	.265
100-199% FPL	-1.57	0.21	0.95	-1.65	.099	-1.44	0.24	0.91	-1.57	.116	-1.23	0.29	0.94	-1.30	.192
200-399% FPL	-0.78	0.46	0.75	-1.03	.301	-0.05	0.95	0.75	-0.07	.945	0.43	1.54	0.88	0.50	.621
Highest education in the household: Reference level = college and above															
Less than high school	6.24	511.79	2.70	2.31	.021	6.95	1040.70	2.63	2.64	.008	5.80	330.44	2.78	2.09	.037
High school or GED	1.70	5.49	1.03	1.66	.097	0.68	1.98	1.01	0.67	.501	0.73	2.07	1.03	0.71	.480
Some college or technical school	0.98	2.66	1.07	0.92	.359	0.81	2.24	1.04	0.77	.440	0.48	1.62	1.14	0.42	.671
Child Sex: Reference group = Male	-1.21	0.30	1.22	-0.99	.322	-2.22	0.11	1.20	-1.86	.063	-1.65	0.19	1.46	-1.13	.259
Child age	0.10	1.11	0.11	0.94	.345	-0.02	0.98	0.11	-0.15	.879	0.00	1.00	0.11	-0.04	.968
Latinx, Hispanic*RSV	-	-	-	-	-	-	-	-	-	-	0.03	1.03	0.04	0.81	.416
Black, non-Hispanic*RSV	-	-	-	-	-	-	-	-	-	-	-0.04	0.96	0.05	-0.85	.396
Asian, non-Hispanic*RSV	-	-	-	-	-	-	-	-	-	-	0.16	1.18	0.11	1.50	.134
Other/Multi-racial, non-Hispanic*RSV	-	-	-	-	-	-	-	-	-	-	-0.14	0.87	0.10	-1.43	.152
RSV	-	-	-	-	-	0.01	1.01	0.00	3.97	< .001	0.02	1.02	0.01	2.02	.044
	Random Effect (variance)					Random Effect (variance)					Random Effect (variance)				
State (Intercept)	0.002					<.001					<.001				

Note. RSV = state-level relative search volumes. FPL = federal poverty line. Coef = coefficient. OR = Odds Ratio.

V. FIELD STATEMENT

Mental illness is a major cause of disease burden worldwide (Erskine et al., 2015; Whiteford et al., 2013). Reducing burden relies on accessible and effective interventions that can reach families in need of services (Kazdin & Blase, 2011). Despite significant advances in evidence-based practice, youth with mental health diagnoses remain underserved (Merikangas et al., 2011) and sociodemographic inequities in access to care are high (Cook et al., 2019). High illness burden, low service utilization, and persistent disparities point to questions about public access to care and information.

Prior examination of facilitators of and barriers to help-seeking pathways (Eiraldi et al., 2006; Reardon et al., 2017) points to the importance of conducting ethnoculturally inclusive research. In recent years, there has been increasing interest in public health models of care (Atkins & Frazier, 2011), population-level trends (Xu et al., 2018), and geographical variations in service utilization (Fulton et al., 2009, 2015; Piper et al., 2018). However, most studies presume families have adequate and equitable information about mental health that would inspire diagnosis- and treatment-seeking behaviors. Families often start with internet searches prior to accessing care and continue seeking information online through different help-seeking stages, highlighting the need for understanding information inequities.

Google, as the most popular public search engine (Statcounter, 2020), and big data tools, with its recent application in personalized care (Cohen et al., 2020), offer the opportunities for understanding, improving, and transforming systems of care in the current internet era. Google Trends is a viable tool to understand public interest and online information-seeking patterns, offering insights into clinical care and policies

(Arora et al., 2019; Ayers et al., 2013; Gunn III et al., 2020). We reported online information-seeking trends, seasonality and the impact of media events related to ADHD and its treatment, suggesting allocating resources toward mental health advocacy and school-based dissemination (see Chapter 2). Reported connections between state-level online information-seeking patterns and ADHD diagnosis in youth (see Chapter 3 and Chapter 4) were consistent with prior findings that online information is increasingly important for care in youth-serving settings (Bussing et al., 2012; Pehora et al., 2015; Sage et al., 2018).

Findings reveal several future research directions. First, quality of mental health information online varies, and notably a large percentage of service-seeking parents reported starting with public search engine and experiencing challenges in evaluating and filtering information (Pehora et al., 2015; Rosenblum & Yom-Tov, 2017; Yu et al., 2019). In addition to improving quality of mental health information online (e.g., Helping Give Away Psychological Science initiative; mentioned in Chapter 2), there is an urgent need to understand (temporal and geographical) variations in filtering, consuming and utilizing mental health information. Such research will help identify underserved groups who experience difficulty accessing *empirically supported* information sources. Relatedly, as mentioned in Chapter 3, we propose parabola-shaped relations between information need and access; the ability and willingness of information-filtering could an important 3rd dimension. Recall we propose an optimal point between low psychological literacy and interest (e.g., "I know nothing and do not know what to search") and information overload (e.g., "I know enough," "My head is swimming"), thereby forming an *inverted-U curve*. If we can use search engine data and big data algorisms to identify the aforementioned optimal points for a geographical region on a given mental health topic, we may be able to increase the efficiency and cost-effectiveness of internet-based dissemination strategies.

Second, given the cross-sectional nature of our data (Chapter 3 and Chapter 4), we were not able to examine individual *pathways*. There is a need for understanding potential mediators (e.g., digital skills, self-stigmatization, perceived self-relevancy) and moderators (e.g., information naïve, diagnosis naïve, emotion status) that can explain the impact of information-seeking behaviors on diagnoses and treatment. For example, among treatment- and diagnosis- naïve families, we can invite them to interact with a child confederate (who acted as a typical child with ADHD) and then ask them to use the internet to figure out what has been going on with this child. A qualitative examination of internet browser data will allow us to understand search terms parents used beyond the diagnostic labels (e.g., “ADHD,” “ADHD treatment,” “ADHD medication,” and “ADHD therapy” in the current study) and what websites they have decided to click and browse (Rosenblum & Yom-Tov, 2017). Analyzing the impact of aforementioned mediators and moderators would allow us to understand the unique online information-seeking experience specific to the initial problem recognition stage. Relatedly, a feasibility trial of testing a browser plug-in (to track browser activities) may provide data in naturalistic settings efficiently and offer insights into *timely* dissemination. Future studies can also benefit from a unified multidisciplinary theoretical framework, which incorporates literature from information science (Marton & Choo, 2012; Zimmerman & Shaw, 2020), clinical science (Eiraldi et al., 2006), and public health (Atkins & Frazier, 2011).

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Appendix

Input Features for Machine Learning Models

Variables	Details	Source
Current ADHD diagnoses, all (%)	Percent of children, age 3 through 17, diagnosed with ADD/ADHD	National Survey of Children's Health, Health Resources and Services Administration, Maternal and Child Health Bureau
Current ADHD diagnoses, rated mild (%)	Percent of children, age 3 through 17 years, with current mild ADHD/ADD	National Survey of Children's Health, Health Resources and Services Administration, Maternal and Child Health Bureau
Current ADHD diagnoses, rated moderate/severe (%)	Percent of children, age 3 through 17 years, with current moderate or severe ADHD/ADD	National Survey of Children's Health, Health Resources and Services Administration, Maternal and Child Health Bureau
Current ADHD treatment, medication (%)	Percent of children, age 3 through 17 years, taking medication for ADD or ADHD	National Survey of Children's Health, Health Resources and Services Administration, Maternal and Child Health Bureau
Current ADHD treatment, psychosocial (%)	Percent of children, age 3 through 17 years, having receive behavioral treatment for ADD or ADHD, such as training or an intervention that you or this child received to help with his or her behavior	National Survey of Children's Health, Health Resources and Services Administration, Maternal and Child Health Bureau
Children with special care needs (%)	Percent of children, age 0 through 17, with special health care needs	National Survey of Children's Health, Health Resources and Services Administration, Maternal and Child Health Bureau
Parent-reported unmet need (%)	Percent of children, age 3 through 17, with a mental/behavioral condition who needed treatment, did not receive it	National Survey of Children's Health, Health Resources and Services Administration, Maternal and Child Health Bureau
Avoided care due to cost (%)	Percent of adults who reported a time in the past 12 months when they needed to see a doctor but could not because of cost	Behavioral Risk Factor Surveillance System, Census Bureau
1 or more preventive visit (%)	Percent of adolescents, age 12 through17 years, with a preventive medical visit in the past year	National Survey of Children's Health, Health Resources and Services Administration, Maternal and Child Health Bureau
Children living in poverty (%)	Percent of children younger than 18 years who live in households below 100% poverty threshold	American Community Survey, US Census Bureau
Median income ($)	Median Annual Household Income	American Community Survey, US Census Bureau
Per capita income ($)	Per capita income in the past 12 months, in inflation-adjusted dollars to data year	America Health's Ranking
Youth residing with > 1 unemployed parent (%)	Percent of children under age 18 living in families where at least one parent does not have a job, has been actively looking for work in the past 4 weeks, and is currently available for work.	Current Population Survey Basic Monthly Data Files, US Census Bureau, Kids Count data center, Annie E. Casey Foundation

Unemployment rate (%)	Percent of civilian population, age 16-64, unemployed	American Community Survey, U.S. Census Bureau, America Health's Ranking
Uninsured population (%)	Percent of population that does not have health insurance privately, through an employer or through the government	American Community Survey, U.S. Census Bureau, America Health's Ranking
Uninsured youth (%)	Percent of youth, age under 19 years, that are uninsured	Small Area Health Insurance Estimates (SAHIE), US Census Bureau
Private insurance only (%)	Percent of civilian population on insurance that are employment-based (plan provided through an employer or union) or directly purchased (coverage purchased directly from an insurance company or through a federal or state marketplace (e.g., healthcare.gov)	American Community Survey, US Census Bureau,
SSI beneficiaries in population	Percent of population who are SSI beneficiaries	Kaiser Family Foundation
Non-Hispanic Asian (%)	Percent of youth who are Non-Hispanic Asian	American Community Survey, US Census Bureau, Kaiser Family Foundation
Non-Hispanic Black (%)	Percent of youth who are Non-Hispanic Black	American Community Survey, US Census Bureau, Kaiser Family Foundation
Non-Hispanic Multiracial (%)	Percent of youth who are Non-Hispanic Multiracial	American Community Survey, US Census Bureau, Kaiser Family Foundation
Non-Hispanic White (%)	Percent of youth who are Non-Hispanic White	American Community Survey, US Census Bureau, Kaiser Family Foundation
Hispanic or Latinx (%)	Percent of youth who are Hispanic or Latinx	American Community Survey, US Census Bureau, Kaiser Family Foundation
American Indian, Alaskan Native or Native Hawaii (%)	Percent of youth who are American Indian, Alaskan Native or Native Hawaii	American Community Survey, US Census Bureau, Kaiser Family Foundation
Medicaid/CHIP apps can be submitted by phone (Y/N)	A binary variable indicates whether individuals can complete Medicaid applications over the telephone at the state level, either through the Medicaid agency or the SBM without being required to send a follow-up paper form or electronic signature to complete the application	Kaiser Family Foundation
Medicaid/CHIP online application can be submitted on mobile devices (Y/N)	A binary variable indicates whether individuals can submit online Medicaid applications using mobile phone	Kaiser Family Foundation
Medicaid/CHIP website mobile-friendly design (Y/N)	A binary variable indicates whether Medicaid applications are mobile friendly	Kaiser Family Foundation
Medicaid/CHIP mobile app available (Y/N)	A binary variable indicates whether mobile applications are available for online Medicaid application	Kaiser Family Foundation
Medicaid eligibility, minimum income ($)	Medicaid income eligibility limits for children age 6 to 18	Kaiser Family Foundation
Elementary school entry age (years)	Compulsory school age specified in state statute.	National Center for Education Statistics
Public assistance (%)	Population of children under age 18 in families that receive SSI, cash public assistance income, or Food Stamps/SNAP.	American Community Survey, US Census Bureau, Kaiser Family Foundation
SSI payments per recipient ($)	Average monthly payment for SSI beneficiaries	Kaiser Family Foundation
Public health funding ($)	State dollars dedicated to public health and federal dollars directed to states per person by the Centers for Disease Control and Prevention and the Health Resources & Services Administration	Annual Estimates of the Resident Population, America Health's Ranking
Pediatricians per 10,000 children, age 70 and under	US-Based certified general pediatricians, age 70 and under	The American Board of Pediatricians
Mental health providers per 10,000 population	Number of psychiatrists, psychologists, licensed clinical social workers, counselors, marriage and family therapists, advanced practice nurses specializing in mental	America Health's Ranking

	health care as well as providers that treat alcohol and drug abuse per 100,000 population	
Primary care physicians per 10,000 population	Number of active primary care physicians (including general practice, family practice, obstetrics and gynecology, pediatrics, geriatrics and internal medicine) per 100,000 population	America Health's Ranking
Active physicians, age 39 or younger (%)	Percent of active physicians by selected age groups, age 39 or younger	Association of American Medical Colleges
Active physicians, age 60 or older (%)	Percent of active physicians by selected age groups, age 60 or older	Association of American Medical Colleges
Access to broadband internet (Y/N)	Percent of individuals with home broadband connection	American Community Survey, US Census Bureau,
K-12 mandatory computer science education (Y/N)	Adoption of at least one of the three K–12 Computer Science Standards: 1) considered to have K–12 CS s cover elementary, middle, and high school; 2) are publicly accessible on the state's website, and 3) include CS content at all levels (elementary, middle, and high school)	The Bank of New York Mellon (BNY) Corporation

Note. ADHD = attention-deficit/hyperactivity disorder. ADD = Attention Deficit Disorder. SSI = Supplementary Security Income. CS = Computer Science. CHIP = Children's Health Insurance Program. Y/N = Yes or No.

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2021-2022	Clinical Psychology Predoctoral Internship-General Child Track University of Washington, Seattle
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