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The trajectories of online mental health information seeking: Modeling search behavior before and after completion of self-report screens

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ABSTRACT

There is an appreciable mental health treatment gap in the United States. Efforts to bridge this gap and improve resource accessibility have led to the provision of online, clinically-validated tools for mental health self-assessment. In theory, these screens serve as an invaluable component of information-seeking, representing the preparative and action-oriented stages of this process while altering or reinforcing the search content and language of individuals as they engage with information online. Accordingly, this work investigated the association of screen completion with mental health-related search behaviors. Three-year internet search histories from $N = 7572$ Microsoft Bing users were paired with their respective depression, anxiety, bipolar disorder, or psychosis online screen completion and sociodemographic data available through Mental Health America. Data was transformed into network representations to model queries as discrete steps with probabilities and times-to-transition from one search type to another. Search data subsequent to screen completion was also modeled using Markov chains to simulate likelihood trajectories of different search types through time. Differences in querying dynamics relative to screen completion were observed, with searches involving treatment, diagnosis, suicidal ideation, and suicidal intent commonly emerging as the highest probability behavioral information seeking endpoints. Moreover, results pointed to the association of low risk states of psychopathology with transitions to extreme clinical outcomes (i.e., active suicidal intent). Future research is required to draw definitive conclusions regarding causal relationships between screens and search behavior.

1. Introduction

Mental disorders are highly prevalent, impacting nearly one in five people annually in the United States (NIMH, 2022). Common mental disorders, such as anxiety and depression, impose considerable social and economic burden, ranking in the top 20 causes of disability worldwide (Global Burden of Disease Collaborative Network, 2020) and representing the largest single contributor to years lived with disability (Whiteford et al., 2013). Moreover, mental disorders worldwide cost an estimated 2.5 trillion U.S. dollars, a value expected to increase to six trillion U.S. dollars by 2030 (Bloom et al., 2011). The influence of mental disorders on personal burden is also extensive and multi-faceted, fueling detrimental outcomes related to stigma and discrimination (Eylem et al., 2020), social support (Thoits, 2011), and suicidal behaviors (Chesney et al., 2014), to name a few. Despite this, fewer than one half (46%) of U.S. adults with a mental disorder receive treatment (SAMHSA, 2020). The cause of this treatment gap is complex and multifactorial, though evidence suggests that attitudinal barriers heavily contribute to the deficit, most notably those that reflect a lack of perceived need for treatment (Andrade et al., 2014; Kessler et al., 2001;

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Mojtabai et al., 2011). In turn, such attitudes may broadly stem from low levels of mental health literacy (Brijnath et al., 2016). Narrowing the mental health treatment gap may therefore be possible through broadening access to reliable and personal mental health information.

In this regard, mental health screens have become an increasingly popular tool for providing individuals with personal mental health information. Broadly speaking, screens are self-report questionnaires, derived from clinically administered and psychometrically-validated inventories, that aim to provide automatic feedback regarding the severity of a specific mental health condition (Jacobson et al., 2022). Importantly, screens function to facilitate information-seeking and promote treatment- and help-seeking capabilities (Lee et al., 2022). With the ubiquity and connectivity of modern technology, mental health screens have become increasingly accessible through online means. Consequently, these "digital screens" function as a primary step in the process of information seeking behavior for individuals concerned or uncertain about their mental wellbeing (Jacobson et al., 2022; Lee et al., 2022). Within the context of health information-seeking behavior models, digital screens are an invaluable resource during bouts of active information seeking (Longo, 2005) with associated implications for the contemplation and preparation stages of health behavior change (Wathen & Harris, 2005). Moreover, Miller's Monitoring and Blunting Hypothesis (Miller, 1987) posits that active information seekers benefit from the ability to gather massive amounts of information during information seeking which allows them to more readily accept their disease and adapt through health care and prevention measures (Lalazaryan & Zare-Farashbandi, 2014). In this light, digital screens may be especially important as facilitators of active self-monitoring which, in turn, may adjust attitudes to encourage further medical action and downstream positive maintenance.

Indeed, mounting empirical evidence suggests that electronically-administered mental health screens are a powerful tool that can increase awareness and alter outcomes. For example, one work found that a digital mental health screening tool administered in general practitioners' waiting rooms increased the identification of anxiety or depressive symptoms that were not previously identified as well as subsequently increased the prescription of, and adherence to, digital mental health interventions (Whitton et al., 2021). Another study leveraged internet search data following completion of online mental health screens and revealed that screen results were predictive of ensuing help-seeking behaviors (Jacobson et al., 2022). In a third work, college students who completed an online mental health screen where they received group-tailored feedback based on their results experienced a reduced individual burden in seeking mental health care and a mitigation of negative responses following screen completion (Lee et al., 2022).

Despite these positive outcomes, there is also some evidence showing that online screening tools can be detrimental when utilized by persons with mental disorders. For instance, one work showed reductions in "professional service use" among individuals with social anxiety after completing a screening questionnaire (Batterham et al., 2016), while another study demonstrated that individuals who received screens with referrals to in-person care were more likely to make search queries related to suicidal intent (Jacobson et al., 2022). Another investigation also highlighted a general inefficacy of online screeners to promote help-seeking behaviors, and found that individuals with a history of poor mental health were less likely to follow links to online symptom-related resources provided upon screen completion (Choi et al., 2018). Taken together, while there is both theoretical and empirical support in the literature for online mental health screens to serve as positive behavioral catalysts toward more active treatment-seeking, evidence for or against this role remains circumstantial and inconsistent.

Nevertheless, the majority of studies to date on digital screens have occurred within the research setting where screens are a mandatory prescription rather than a voluntary or unguided option. Moreover, meta-analyses have indicated that the context in which individuals interact with mental health resources, including digital screens, can significantly influence their experiences and outcomes (Borghouts et al., 2021; Perski et al., 2017). Accordingly, a more naturalistic characterization of screens' impact as a component of the mental health information-seeking process is warranted. One way to address this impact more satisfactorily is through the interrogation of other information-seeking behaviors that are coincident and proximal in time to digital screen utilization. Given the availability of digital screens on the internet, online search behavior is a common form of contemporary information-seeking that occurs alongside screen utilization and is therefore a highly relevant and contextually rich signal to consider. The majority of people under 25 years old perform internet search queries as their primary method of seeking mental health information and help, with cited benefits of internet searching including anonymity, ease of access, and autonomy over one's help-seeking journey (Pretorius et al., 2019). Furthermore, online search behavior has been leveraged to good effect within mental health research. Various works have uncovered significant associations of internet search behavior with anxiety (Hamamura & Chan, 2020), depression, and suicide (Bruckner et al., 2014) and have suggested a prominent role of online searches in mental health self-diagnosis (Aboueid et al., 2021; Jacobson et al., 2022). Taken together, the literature implicates online search data as a unique lens to observe the general and personal experience of mental disorders. Importantly, this lens affords an ability to study the longitudinal, densely-represented digital traces of an individual which can be ultimately leveraged to model progression through the treatment-seeking process and offer opportunities for intervention and recovery support.

The current work combined Microsoft Bing user search query data with associated records of completed online mental health screens available through Mental Health America (https://screening.mhanational.org/screening-tools/), a nationwide, non-profit mental health advocacy and support organization (MHA, 2023). Internet users who completed clinically validated MHA digital screens for depression, anxiety, bipolar disorder, or psychosis were linked with their temporally proximal search history to interrogate behavioral changes as a function of screen completion. Modeling this data within a network-based analytical framework, the current work sought to answer the following primary questions.

(i) What differences exist between the overall search behavior of screen completers with lower and higher categories of self-report disorder severity?
(ii) Do patterns in online search behavior differ from before to after first completion of an online mental health screen?
(iii) What are the most likely long-term search behaviors of users after first completion of an online screen?
(iv) Is there evidence to support a tentative association between online screen completion and overall mental health-related search behavior?

2. Methods

2.1. Cohort description and data collection

The current study leveraged data from Microsoft Bing and Mental Health America (MHA). With an estimated 100 million users and 6.2 billion monthly searches, Bing comprises over one-third (38.2%) of the search engine market share in the U.S. (Microsoft, 2022). Moreover, past research found strong correspondence between U.S. county-level census counts and the number of Bing users (Yom-Tov, 2017) and between Bing and Google users (Rosenblum & Yom-Tov, 2017).

Queries submitted to the Bing search engine from users in the U.S. over a period of three years beginning on January 1, 2020 were first extracted from Bing's records. For each query, (i) date and time, (ii) text content, (iii) anonymized user identification, (iv) pages clicked by the user, and (v) the county from which the user submitted their query was obtained. Second, records of all anxiety, bipolar, depression, eating disorder, psychosis, and PTSD screens completed by individuals on the MHA website who were directly referred via Bing during the same three-year time frame were extracted from MHA's records. Each screen is freely accessible, confidential, anonymous, and based on the following scientifically and psychometrically validated questionnaires: Generalized Anxiety Disorder 7-item (GAD-7) (Spitzer et al., 2006), Mood Disorder Questionnaire (MDQ) (Hirshfeld, 2002), Patient Health Questionnaire 9-item (PHQ-9) (Kroenke et al., 2001), Stanford-Washington Eating Disorder Screen (SWED) (Graham et al., 2019), Prodromal Questionnaire—Brief (PQ-B) (Loewy et al., 2011), and Primary Care PTSD Screen for DSM-5 (PC-PTSD-5) (Prins et al., 2016). Relevant to the current study, each MHA record consisted of (i) screen type, (ii) date and start time of the screen, (iii) user gender, (iv) user race, (v) user household income, and (vi) indications of current and past mental health diagnosis and treatment.

Users were identified via browser cookies which were provided as anonymous user identifiers to the researchers. However, if a user cleared their cookies or made use of an anonymous browsing window (i.e., "private browsing") they would appear as a new user. Nevertheless, this strategy afforded the ability to know, with high probability, that any two queries were from the same user. MHA data were linked to Bing user identifiers by finding a user who clicked on the same webpage as that of the screen within 5 min of the start time indicated by MHA. From these users, the time of each Bing query relative to the time of the MHA screen was computed, and data was discarded if more than one access from Bing was found or if multiple screens from the same topic were started on MHA within the same 5-min time window. These measures were taken to ensure the unique identification of each user. Queries of each user (as identified by their anonymized user identifier) were retained from a maximum of one year prior to the completion of their first MHA screen and until one year after initial screen completion. On average, users were active for 94 days prior to the completion of the screen and 80 days after it.

This study and associated protocol were deemed to present no greater than minimal risk to subjects and thus "exempt" from further review by the Committee for the Protection of Human Subjects at Dartmouth College. The study was further approved through a full review process made by the Microsoft Institutional Review Board. Microsoft's Institutional Review Board considers Bing's terms of use in decision making, wherein research is designated as a possible use of data. Accordingly, use of Bing is considered sufficient consent in the case of this work.

2.2. Search behavior topic categories

To characterize online mental health search behavior, queries were categorized into seven distinct (but not mutually exclusive) classes of content, plus two additional behaviors (screen completion and cessation of searching which are described in 2.3.2 below). These first seven categories were selected based on scope and previous success in utilization, specifically their close alignment with the current work's content area of mental health information seeking as well as their demonstrated ability to be reliably codified (Jacobson et al., 2022). Lists of terms and phrases for all categories were first developed through manual curation and expert input from both a licensed psychiatrist and clinical psychologist. For all categories except "Treatment", these lists were then used to train and validate a series of logistic regression models which were leveraged to classify the category membership of more uncommon queries. Details on this process are available in a previous work (Jacobson et al., 2022). Table 1 provides a description of each category alongside an example query, the mode of identification, and volume of data (users and queries) represented by each category.

2.3. Data preprocessing

2.3.1. Screen score stratification

User screen completion data for each of anxiety (GAD-7), bipolar (MDQ), depression (PHQ-9), and psychosis (PQ-B) consisted of severity labels which defined the raw score attained. Data for eating disorder (SWED) and PTSD (PC-PTSD-5) were not analyzed due to low rates of completion in the cohort. The following sections describe the scoring of each screen and how scores were transformed into binary stratified samples for subsequent analysis.

2.3.1.1. Anxiety. The GAD-7 is a seven-item screen which asks how often an individual has been bothered by problems over the past two weeks. where each item ranges from 0 ("not at all") to 3 ("nearly every day") on a Likert scale, and the sum scores assume the categories of "mild" (0–4), "minimal" (6–9), "moderate" (10–14), and "severe" (15–21). These labels were used for the basis of stratifying the cohort of users into two groups: those who reported mild or minimal anxiety (<10) and those who reported moderate to severe anxiety (≥ 10).

2.3.1.2. Bipolar. The MDQ consists of five main questions, the first of which consists of 13 "yes"/"no" items and the third of which asks the participant to rate the degree to which their endorsed items caused a

Table 1
Description and data representation of query content categories.

Query Category (Abbreviation)	Description of Query Contents	Example	Method of Identification	User Count	Total Queries
Diagnosis (DIA)	Search affirms condition	"i have depression"	Pattern matching: "i have/i've been diagnosed" + Logistic regression model[a]	5101	50,613
I-My (IMY)	Search contains "i" or "my" but does not affirm condition	"do i have bipolar"	Pattern matching: "i" or "my" + Logistic regression model[a]	5422	131,389
Psychoactive Medications (DRU)	Search contains prescription drugs commonly associated with depression, anxiety, bipolar disorder, or psychosis	"risperidone side effects"	Curated list of drug names by trade name[b] + Logistic regression model[a]	1555	12,650
Treatment (TRT)	Search is an appeal for professional help	"psychiatrist near me"	Curated list of terms	3368	35,792
Suicide Active Intent (SAI)	Search signifies present desire to commit suicide	"i want to kill myself"	Logistic regression model[a]	1748	6632
Suicide Passive Ideation (SPI)	Search endorses thoughts of suicide or wishing to be dead, but does not contain language signifying intent to act on these thoughts	"i hate being alive"	Logistic regression model[a]	341	872
Suicide Help-Seeking (SHS)	Search is an appeal for resources or aid regarding suicidality	"suicide hotline"	Logistic regression model[a]	651	1319

Note.
[a] Category-specific binary classification model trained and validated on a curated list of common queries and applied to uncommon queries to predict category membership as successfully implemented and discussed in a previous work (Jacobson et al., 2022).
[b] List is based on psychoactive medications provided in Stahl's Essential Pharmacology (Stahl et al., 2017).

problem (ranging from "no problem"—"serious problem"). Responses are assessed as either "bipolar negative" or "bipolar positive", the latter of which is assigned if seven or more items are endorsed from question 1, question 2 is endorsed, and at least "moderate problem" is selected for question 3. The cohort was directly stratified into two groups based on this binary state.

2.3.1.3. Depression. The PHQ-9 is a nine-item screen which asks how often an individual has been bothered by problems over the past two weeks. Each item response ranges from 0 ("not at all") to 3 ("nearly every day") on a Likert scale, and the sum scores assume the categories of "mild" (0–4), "minimal" (5–9), "moderate" (10–14), "moderately severe" (15–19), and "severe" (20–27). These labels were used for the basis of stratifying the cohort of users into two groups: those who reported mild or minimal depression (<10) and those who reported moderate to severe depression (≥10).

2.3.1.4. Psychosis. The PQ-B is a 21-item screen which asks whether or not the participant had specific thought, feelings, and experiences in the past month, and if so, the level of distress ("When this happens, I feel frightened, concerned, or it causes problems for me") experienced as a result (ranging from "strongly disagree"—"strongly agree"). Each of these items thus ranges from 0 to 5 on the Likert scale with 0 indicating no endorsement and 5 indicating high distress endorsement. A score ≥6 indicates possible risk for psychosis. This scheme was used to directly stratify the cohort into low/no risk (<6) and possible risk for psychosis (≥6).

2.3.2. Operationalization of user search behavior

The sequence of queries made was analyzed by calculating the percentage of users who query in category *j* after querying in category *i* (i.e., the probability of transitioning to *j* given all possible transitions from *i*) as well as the average time elapsed, in days, between each transition from *i* to *j* (timing to transition). This approach was implemented with user stratification by screen type (anxiety, bipolar, depression, psychosis) and score severity (see above) as well as whether the queries were made before or after the user's first completed screen. From the seven content categories (see Table 1), additional "Questionnaire" (QST) and "Stoppage" categories (STP) were added, totaling nine search behavior categories. QST was assigned in the search sequence based on the recorded timestamp of a screen completion, and STP was assigned when a user ceased to query for more than one standard deviation above the mean time between their queries. To allow for the computation of error bounds, we repeated all calculations through bootstrapping where 90% of the data was resampled without replacement at each iteration (k = 1000).

2.4. Network visualization

Using data generated from 2.3.2, query categories were modeled as nodes in a network where edges represented weighted, directional transitions from one category to another. Two network types were generated per screen and severity stratum (16 total) using the *networkX* package (Hagberg et al., 2008) in Python (v3.9). The first type weighted the edges based on the average transition probabilities across the 1000 bootstrapped networks and the second weighted the edges based on the inverse of the average transition times. Accordingly, edges with higher weight denote search transitions that are more likely or quicker in succession relative to edges with lower weight. These networks incorporated search behavior data from both before and after first completion of a screen and thus were agnostic to this event.

2.5. Network statistics and analysis of change

Probability and time networks sensitive to the timing of first screen completion (before or after) were also generated from the bootstrapped data. This yielded 3200 networks, 1600 of which were probability-based and 1600 of which were time-based (2 network types*4 screen types*2 severity strata*2 screen completion timing*1000 resamples = 32,000). To assess changes from before to after first screen completion, four commonly employed network node statistics were calculated: (i) betweenness centrality, (ii) closeness centrality, (iii) in-degree, and (iv) out-degree. Significant change in a node statistic from before to after first completion of a screen for a given network type, screen type, and severity combination (e.g., the before and after probability networks of negative bipolar), was assessed through comparison of respective 95% confidence interval estimates around the node statistic which were derived from the bootstrap resamples. Changes were not deemed significant if there was overlap between the 95% confidence interval of the "before" network and the 95% confidence interval of its corresponding "after" network.

2.6. Markov chain simulations

A Markov Chain is a model of a stochastic process whereby the probability of event sequencing is determined solely on the current state of the system (Gagniuc, 2017). This "memoryless" system proceeds in discrete time steps and transitions from one state to another with some probability within a defined state space. A Markov Chain therefore manifests as a directed graph with nodes as states and weighted edges as transition probabilities. One way to interrogate the behavior of this system is to ascertain its long-term steady-state distribution—the point in the "random walk" process where the probability of being in any one state no longer changes. Both structurally (a network) and dynamically (a sequence), the Markov Chain is an appropriate framework with which to model the process of search behavior.

Akin in principle to a time-inhomogeneous Markov Chain, where the transition probabilities are not fixed through time (Vassiliou, 2022), probability and time-to-transition data from each screen and severity stratum were reconciled to simulate movement through a finite state space of nine possible search behavior states and determine the steady-state distribution. One thousand simulations on data from each of eight screen-severity combinations were run. The state probabilities at each step were averaged across the 1000 simulations and visualized. Discrete steps in the process represented days, and each simulation was specified to run for twice as long as the longest recorded transition in the data, increasing the likelihood of detecting steady-state convergence. Example commented Python code for these simulations is available as Supplementary File 2.

2.7. Data availability

The network data generated in 2.3.2 from raw user search behavior is provided as Supplementary File 1. This data includes the bootstrapped probabilities and times to transition for each pair of search topic nodes across all screens (anxiety, bipolar, depression, and psychosis) and binarized severity strata. Accordingly, this data can be utilized by readers to replicate the results described herein or to conduct complementary or additional analyses if desired. However, due to the sensitive nature of the data, and to ensure the maintenance of anonymity, the raw user data is not provided.

3. Results

3.1. Cohort characteristics

The process of data collection yielded 41,462 MHA questionnaires, where a third of these (13,584) were matched to a Bing query. Of these matches, N = 7572 (56%) represented unique users. The four most popular screens (anxiety, bipolar, depression, and psychosis) were considered in further analyses. Table 2 provides a breakdown of

Table 2
Cohort sociodemographics by screen type.

Attribute	Value	User Count by Screen Type (% of Cohort)			
		Anxiety $n =$ 1106	Bipolar $n =$ 914	Depression $n =$ 5022	Psychosis $n =$ 297
Gender	Female	689 (62.3)	516 (56.5)	2552 (50.8)	128 (43.1)
	Male	235 (21.2)	224 (24.5)	1660 (33.1)	106 (35.7)
	Other/Not Provided	182 (16.5)	174 (19.0)	810 (16.1)	63 (21.2)
Race	White (Non-Hispanic)	414 (37.4)	408 (44.6)	1872 (37.3)	141 (47.5)
	Asian	144 (13.0)	62 (6.8)	670 (13.4)	17 (5.7)
	Hispanic or Latino	104 (9.4)	69 (7.5)	438 (8.7)	18 (6.1)
	Black or African American (Non-Hispanic)	68 (6.2)	50 (5.5)	313 (6.2)	17 (5.7)
	Other/Not Provided	376 (34.0)	325 (35.6)	1729 (34.4)	104 (35.0)
Household Income	Less than $20,000	171 (15.5)	146 (16.0)	921 (18.3)	51 (17.2)
	$20,000 – $39,999	99 (9.0)	112 (12.3)	547 (10.9)	47 (15.8)
	$40,000 – $59,999	93 (8.4)	101 (11.1)	421 (8.4)	21 (7.1)
	$60,000 – $79,999	58 (5.2)	75 (8.2)	336 (6.7)	17 (5.7)
	$80,000 – $99,999	49 (4.4)	35 (3.8)	242 (4.8)	9 (3.0)
	$100,000 – $149,999	61 (5.5)	58 (6.3)	293 (5.8)	10 (3.4)
	More than $150,000	65 (5.9)	58 (6.3)	315 (6.3)	14 (4.7)
	Not Provided	510 (46.1)	329 (36.0)	1947 (38.8)	128 (43.1)
Ever Diagnosed with Mental Health Condition	No	729 (65.9)	403 (44.1)	3325 (66.2)	125 (42.1)
	Yes	185 (16.7)	355 (38.8)	1013 (20.2)	127 (42.8)
	Unknown	192 (17.4)	156 (17.1)	684 (13.6)	45 (15.1)
Ever Received Treatment/Support for Mental Health Problem	No	700 (63.3)	394 (43.1)	3195 (63.6)	126 (42.4)
	Yes	222 (20.1)	365 (39.9)	1151 (22.9)	127 (42.8)
	Unknown	184 (16.6)	155 (17.0)	676 (13.5)	44 (14.8)
Currently Receiving Treatment/Support	No	108 (9.8)	133 (14.5)	610 (12.1)	49 (16.5)
	Yes	107 (9.7)	220 (24.1)	510 (10.2)	73 (24.6)
	Unknown	891 (80.5)	561 (61.4)	3902 (77.7)	175 (58.9)

sociodemographics by screen type for the cohort of $N = 7572$ matched users. While there is representation across race and household income strata, there is higher representation among users who are White, female, and from households with the lowest income. Most screen completers were never diagnosed with a mental health condition and never received treatment or support for a mental health problem.

3.2. Network Visualization and analysis of change

Figs. 1 and 2 visualize the average probabilities of transition and the average times of transition between query categories for each screen type, respectively. Differences in both presence and magnitude of transitions are observable both within and between screen types. For example, the time to transition from Suicide Self-Help (SHS) to completing a Questionnaire (QST) is much quicker in those with at least moderate depression compared with those with mild or minimal depression (Fig. 2). As another example, there was a high probability of transitioning from Suicide Passive Ideation (SPI) to I-My (IMY) in those with negative bipolar which is absent in those with positive bipolar (Fig. 1). Exact probabilities and transition times which correspond with the network edge weights illustrated in Figs. 1 and 2 are available as tables in Supplementary File 3. Moreover, statistically significant changes to the structure of probability and time networks from before to after a first screen was completed were also observed for all screens and severity strata, suggesting an impact of screen completion on the dynamics of search behavior (see Supplementary File 4 for details).

3.3. Markov state distributions through time

All simulations reached steady-state convergence within 70 steps (days) with trends in the relative probability of ending on a specific search behavior (node) emerging within 14–21 steps (one to two weeks) for all screens and severity strata. As shown in Fig. 3, queries regarding treatment, diagnosis, suicide passive ideation, suicide active intent, as well as stoppage commonly presented among the highest probability endpoints relative to all other search behavior categories. These differences in relative long-term likelihood were also notable between the severity strata of each respective screen. Overall, the results of these simulations based on user search behavior subsequent to screen completion suggest a prospective duality in behavior—one characterized by both continued help-seeking within lower severity strata and suicidal tendency alongside stoppage among the more severe, regardless of screen type.

4. Discussion

The present work leveraged naturalistic internet search behavior alongside outcomes from online mental health screens to model the context and influence of screen completion as a key component of the information-seeking process within a general population of users engaging with online mental health resources. Treating search behavior as ordered states of transition, this work built network representations and simulated Markov processes to uncover the most probable behavioral trajectories that proceed screen completion. Overall, completion of online screens was found to have an impact on the dynamics of querying, both in terms of the likelihood and timing of transitioning from one search type to the next. Moreover, queries involving mental health treatment, diagnosis, suicidal ideation, and suicidal intent commonly emerged as the highest probability behavioral endpoints in information seeking, relative to all other topics.

The importance of several search behaviors, primarily assessed through the network node-based statistics of betweenness and degree centrality, shifted significantly once a screen was completed, suggesting some influence of screens on the information-seeking process (see Supplementary File 4). For example, the in-degree and betweenness of the Treatment node within the depression and psychosis probability networks increased from before to after screen completion regardless of severity, suggesting that these screens led to a higher overall likelihood of transitioning from any other search type to searches for treatment (in-degree) and that treatment searches more frequently connected the most likely pairwise sequence of searches (betweenness). As another example, the Diagnosis node decreased in importance after completing an anxiety screen, regardless of severity; increased in importance after completing a depression or psychosis screen, regardless of severity; and decreased or

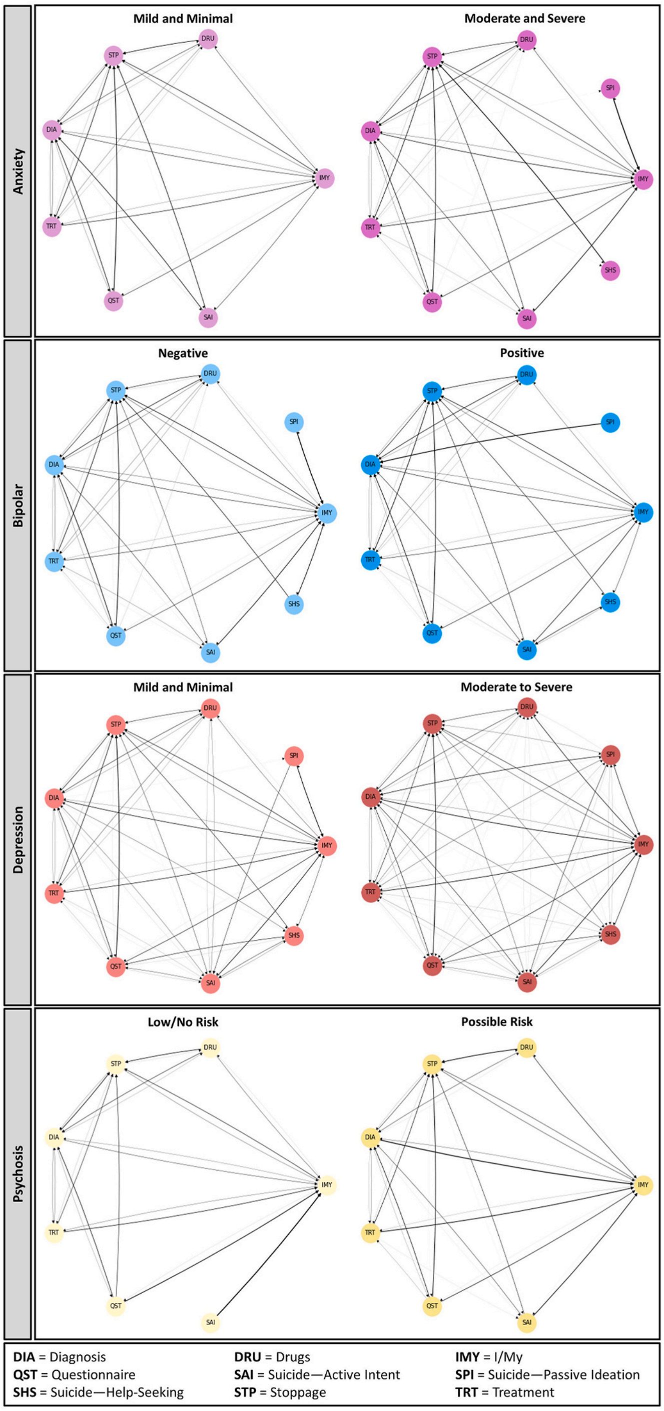

Fig. 1. Networks of Online Search Activity Topics Weighted by Transition Probabilities
Note. All networks are bidirectional. Nodes represent search topics with their associated descriptions provided in Table 1 for reference. Directionality denotes a transition from a search of one topic type directly to a search of another topic type. Edges are weighted by probability, with thicker edges denoting higher probabilities. For clarity, self-directed edges and edges with probability <0.1 are not drawn. For each screen type (anxiety, bipolar, depression, psychosis), cohort data was stratified based on screen result severity as indicated.

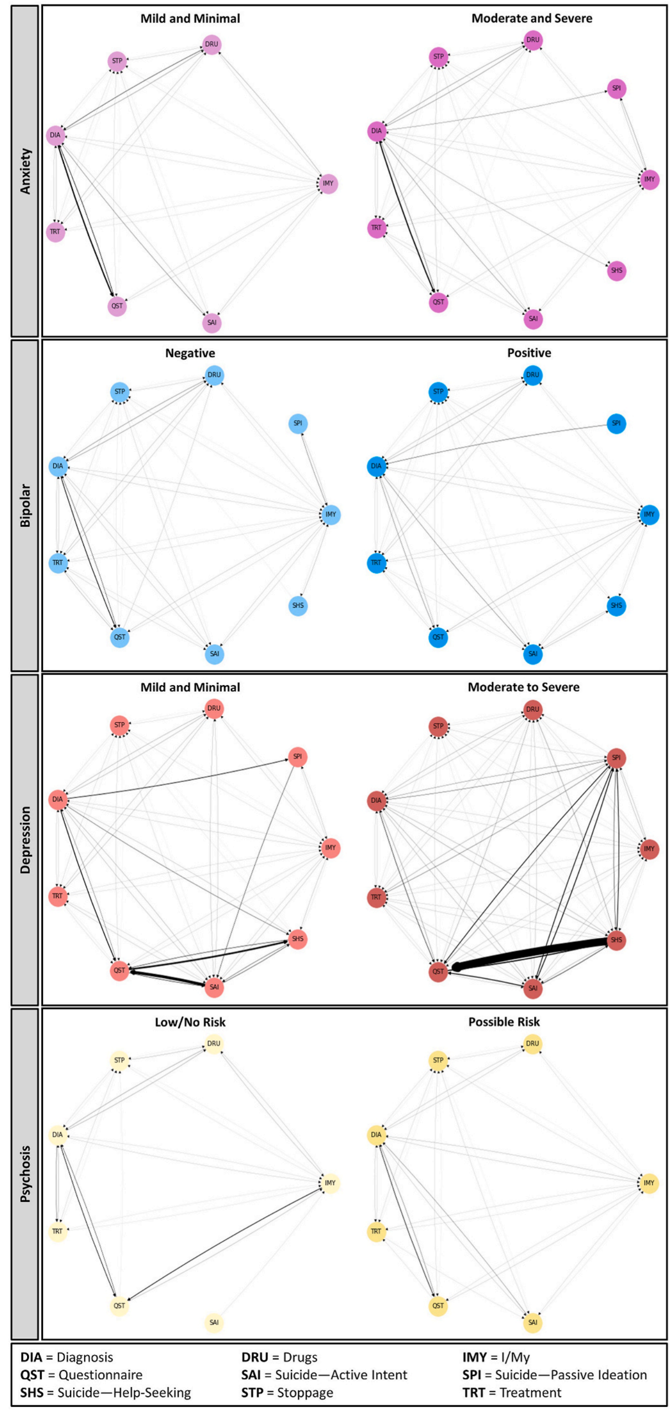

Fig. 2. Networks of Online Search Activity Topics Weighted by Transition Time
Note. All networks are bidirectional. Nodes represent search topics with their associated descriptions provided in Table 1 for reference. Directionality denotes a transition from a search of one topic type directly to a search of another topic type. Edges are weighted by the inverse time between search topic types, with thicker edges denoting lesser time between search topic types. For clarity, self-directed edges are not drawn. For each screen type (anxiety, bipolar, depression, psychosis), cohort data was stratified based on screen result severity as indicated.

increased in importance after completing a bipolar screen if the subject scored within the Negative or Positive stratum, respectively. Interested readers are encouraged to peruse Supplementary File 4, where a complete summary of all network statistics is provided. While the specific potential implications of shifts in importance for each combination of search type, screen completion type, and severity score are beyond the scope of this work, the results generally point to the possibility that screens alter the trajectories of an individual's search procedure. Despite this, the current work cannot, and does not, establish causality, which should be examined in future work. With empirical support for an

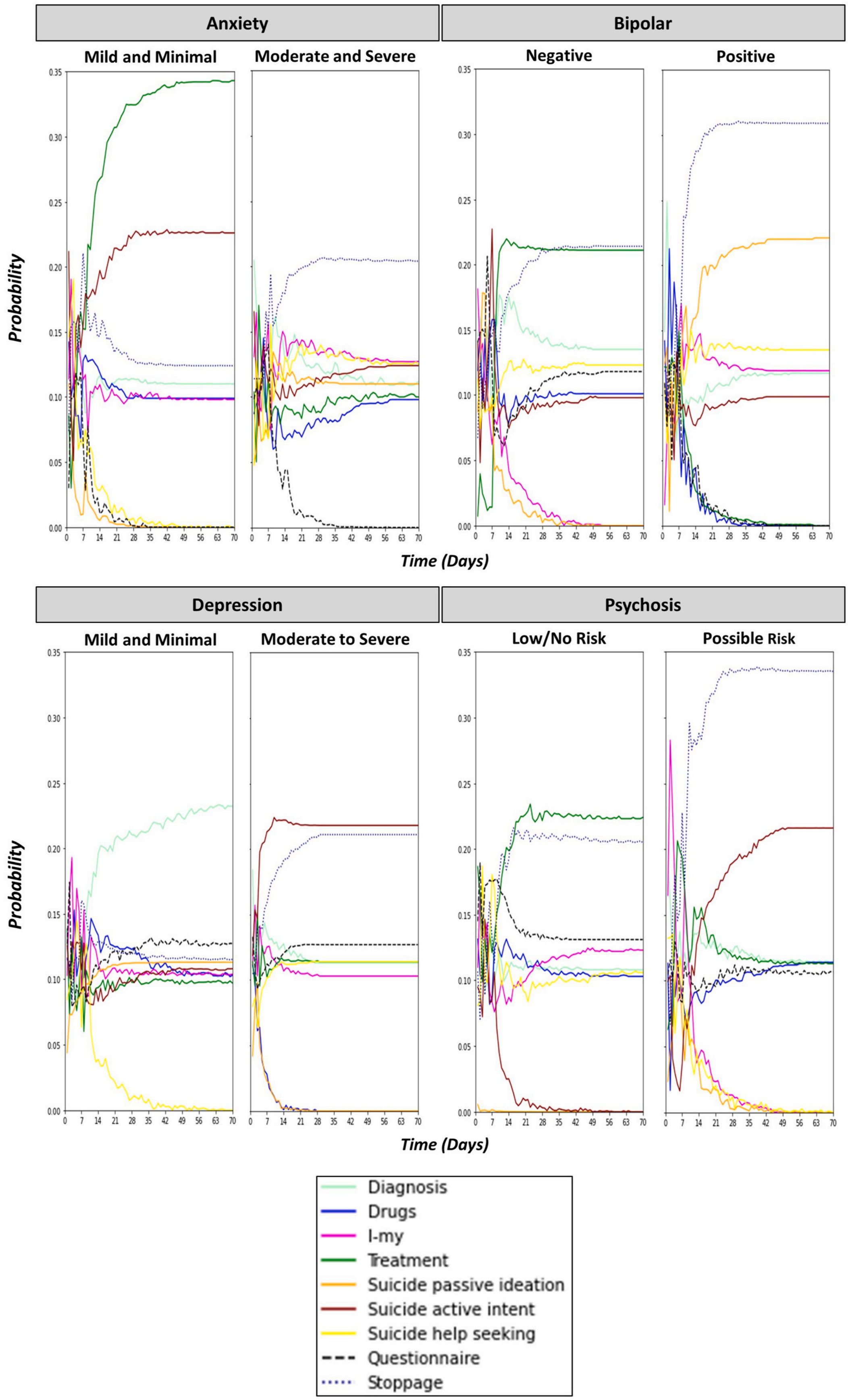

Fig. 3. Markov Chain Simulations of Search Behavior by Screen Type and Outcome Severity
Note. Cohort of individuals completing the anxiety, bipolar, depression, and psychosis screen, stratified into two classes based on the severity of outcome scores. State probability distributions are represented across a ten-week (70-day) simulation.

association between screens and the procedural nature and content of searches, the main question concerned the long-term likelihood of making certain types of searches after completing a screen rather than the nature of the search process itself. In other words, what are the prominent behavioral endpoints of an information-seeking process that has been potentially influenced by completing a screen?

The results from the Markov simulations (Fig. 3) implicate treatment and diagnosis classes of queries as among the most likely endpoints, particularly among the mild depression, low-risk psychosis, and low risk bipolar strata. Echoing the results from the aforementioned before-to-after networks, these endpoints may represent further help-seeking behavior in response to online screen completion, which has mixed support in existing literature. While past work has been limited, some have suggested the capacity of mental health screens to predict (Jacobson et al., 2022) and promote later help-seeking behaviors (Greenfield et al., 1997), while others have reported a negative effect of online mental health resources on subsequent professional help-seeking (Batterham et al., 2016). Interestingly, these help-seeking endpoints were most prominent among persons within the mild or low-risk categories of psychopathology. This finding is inconsistent with other literature suggesting that help-seeking behaviors are positively associated with *higher* symptom burden (Lemma et al., 2022; Mojtabai et al., 2011; Sherwood et al., 2007; Wang et al., 2005). The reasons for this deviation from the broader literature are not clear, but one potential explanation is that receiving lower severity results may serve to promote self-reflection which leads to both an acknowledgement of difficulties (Diagnosis searches) and a recognition of the potential benefits that may result from seeking professional help (Treatment searches). Such catalysis is possible given the potential tendency for less severely symptomatic individuals to possess a greater sense of agency or motivation. For those receiving higher scores, the phenomenon of learned helplessness (Maier & Seligman, 1976) may be reinforced, stymying both initiative and motivation. Although plausible, neither self-reflection nor helplessness were measured, thus future work should explore whether these dynamics are indeed occurring within online help-seeking processes.

Along these lines, individuals with more severe self-reported psychopathology were simulated to be highly or most likely to stop all search behavior after completing a screen. While the aforementioned "learned helplessness" is one possible explanation, it is important to note that stoppage may indicate either (i) a true cessation of browsing, either by stopping searches altogether or (ii) a transition to incognito search mode. In the case of the former, stoppage could be due to negative affective symptoms (e.g., anhedonia, reduced motivation) or behavioral disorganization, sufficiently severe to impact desire and/or capacity for online searching. Both anhedonia and disorganization may be present in more severe forms of psychopathology (American Psychiatric Association, 2013). In the latter case, transition to incognito browsing may suggest perceived awareness of one's symptom severity and subsequent desire to hide potentially stigmatizing symptoms. This is in line with the findings presented in Supplementary Fig. 1 (S1), which demonstrate differential rates of incognito browsing according to type of mental disorder, with these rates being generally higher among more stigmatized conditions (e.g., substance use disorder).

Of considerable importance, suicidal intent was found to be the first or second most probable search endpoints in persons with moderate-severe depression, mild-minimal anxiety, and possible risk of psychosis and was more prominent than either passive suicidal ideation or suicidal help-seeking queries. This result bolsters previous predictive work which found that variables describing the attributes of online screens had the largest effect in improving prediction of suicide-related searches (Jacobson et al., 2022). Moreover, these findings support the need to further investigate the short-term effects of (digital) environmental risk for suicidal thoughts and behavior (Franklin et al., 2016). In the broadest sense, these outcomes speak to the risk severity profile of those engaging with online screens—from those initially seeking to better understand and parse their own symptoms, however minor, to those who are actively struggling with one or more conditions. However, to be clear, this work does not posit a causal explanation for any observed associations and trends. Rather, the results signify that those engaging in high-risk suicidal behaviors utilize these online resources, which can help shape the content and presentation of screens to better serve these individuals and mitigate any potential escalation of risk. Further, observed changes in search behaviors following screen completion occurred over a relatively narrow time frame. The emergence of dominant search end points, including suicidal intent, invariably developed within 2–4 weeks after initial screen completion. Future research may benefit from further interrogation of these high rates in query content transitioning.

Probing the nature of the relationship between online mental health screen completion and information-seeking behavior is integral to the creation and ongoing refinement of beneficial content resources online. While the question of whether online mental health screens have a *causal* influence on later behaviors was beyond the scope and means of the current work, the ecologically valid data presented and analyzed herein yielded noteworthy associative trends. Taken together, screen completion and search behavior profiles may serve as useful digital markers for forecasting mental health symptom trajectories. Through future work, if a causal link can be established between screens and behavior, screens could serve as a low-cost and scalable means of affecting behavioral change in persons experiencing mental disorders, potentially at early stages. This far-reaching and cost-effective ability to facilitate both the development of personalized knowledge regarding the nature and severity of mental disorder, as well as to exert a positive influence on subsequent treatment-seeking behaviors, would empower the afflicted and lower the barriers to clinical care receipt. However, in consideration of present and past suicide-related results (Jacobson et al., 2022), empirical support for causality should necessarily prompt efforts to thoroughly investigate and address the potential negative influence of screens on behavior.

This work has several strengths, including a large sample size, the use of objective, naturalistic data with minimal collection burden, and a modeling approach that provides unique introspection into the patterns and trajectories of mental health-related search behaviors. Despite this, there are important limitations to consider. First, our identification of users is imperfect, since, for example, users could appear as new users if they open anonymous browsing windows on their browsers (see also Supplementary File 4). However, for these users there are few, if any, prior and future searches, so their effect on the analysis is minimal. Second, causal relationships between screen completion and mental health search types could not be ascertained. Future research may address this through the use of randomized controlled trials, assigning groups to complete one or more screens. Third, the data itself consisted of search types which are likely imperfect proxies for real mental health behaviors. For example, queries related to suicide are not clear endorsements of suicidal ideation. Fourth, as Markov chain simulations lack memory, the process of navigating a state space does not fully equate to the process of information-seeking, whereby the next query may be a function of both the current query and the previous queries. Relatedly, the current analysis did not consider the information accessed as a result of making a query, which may have significance for search trajectories. Such information could be leveraged using advanced machine learning algorithms, such as the User Behavior Simulator with GAN (Zhao et al., 2021), to more contextually simulate and predict user interaction throughout the online information-seeking process.

Lastly, it is of great importance to discuss the nature of the data utilized in the current investigation. This work leveraged Bing search data which explicitly falls under Microsoft's Terms of Use for "research" purposes. However, despite the necessity to agree to the company's conditions before using Bing, it is likely that most individuals do not consider that their data would be used for any specific research purpose. Such situations are becoming increasingly commonplace within "big data" research paradigms, with questions surrounding how best to handle human subject protection concerns receiving significant attention by researchers and ethicists (Hosseini et al., 2022; Mason & Singh, 2022; Zimmer, 2010). Accordingly, guidelines have been established for Institutional Review Boards to aid in study approval (Office for Human Research Protections, 2015) and previous work has attempted to directly address these ethical quandaries (Yom-Tov & Cherlow, 2020). Taken together, researchers have a moral responsibility to prioritize the well-being of individuals whose data is being used, regardless of any legal definitions or allowances that permit use in the first place. This is especially timely given the relatively recent controversy surrounding the reuse of medically relevant browsing information without explicit consent by users (Das, 2023). In the spirit of scientific transparency, accessibility, and reproducibility, this work makes available as much data as possible (see 2.7); however, the importance of maintaining complete subject anonymity in the absence of explicit consent (Yom-Tov & Cherlow, 2020) precluded the ability to share any individualized sociodemographic or search query data. While this lack of detailed data availability may be perceived as a limitation, this work nonetheless presents one solution to maximizing the advantages afforded by online data while respectfully navigating the ethical challenges they bring to the fore.

The present study is the first to temporally contextualize online mental health information-seeking behavior. Using networks to operationalize and model a large internet sample of naturally occurring search queries alongside data on the completion of clinically validated screens, this work highlighted shifts in search dynamics as a function of screen completion as well as likely search endpoints following screen completion, the latter of which suggested both positive (high relative probability of searches for treatment and diagnosis) and detrimental (high relative probability of searches related to suicidal intent and suicidal ideation) behavioral outcomes 2–3 weeks post screen completion. While future research utilizing more contextually rich datasets and models within randomized controlled trial settings is required to draw definitive conclusions regarding any mechanistic influence of screens on mental health information seeking, there is a demonstrated signal of association which may have implications for longitudinal mental health risk assessment as sought information is found, processed, and acted upon.

Ethics approval

This study and associated protocol were deemed to present no greater than minimal risk to subjects and thus “exempt” from further review by the Committee for the Protection of Human Subjects at Dartmouth College. The study was also further approved by the Microsoft Institutional Review Board.

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CRediT authorship contribution statement

Damien Lekkas: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis. **Elad Yom-Tov:** Writing – review & editing, Software, Methodology, Conceptualization. **Michael V. Heinz:** Writing – review & editing, Writing – original draft. **Joseph A. Gyorda:** Writing – review & editing, Writing – original draft. **Theresa Nguyen:** Writing – review & editing, Resources, Conceptualization. **Paul J. Barr:** Writing – review & editing, Conceptualization. **Nicholas C. Jacobson:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data has been shared as Supplemental File 1 at the Attach File step.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2024.108267.

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