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Topic Modeling of Measurement-Based Care in Behavioral Health Care Using Latent Dirichlet Allocation (LDA)

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Abstract

Measurement-based care (MBC) is the systematic collection of patient-reported measures to monitor treatment progress and inform clinical decision-making. Past research shows that MBC can improve patient engagement and healthcare outcomes, including Behavioral Health-Care (BHC). Despite extensive developments of MBC in physical healthcare within the United States, research shows that only 11% of psychologists and 18% of psychiatrists apply MBC in their therapy. This slow uptake of MBC in BHC motivates our work. There is a growing base of companies today offering MBC products and services to mental health professionals. To better understand how these service providers are trying to shape MBC adoption within BHC, we examined themes from the MBC providers' perspective. Precisely, we captured 1,719 documents from 22 service provider websites, then applied the LDA topic modeling method to identify language patterns and related topics within these documents. To identify the optimal model, we quantitatively analyzed models with Coherence measures and qualitatively with the aid of clinically trained subject matter experts.

The study results identified 15 different topics, which reveals themes that are closely associated with BHC assessment and diagnosis, efforts to manage BHC, financial management, and community BHC.

Keywords: Topic modeling, Latent Dirichlet Allocation, Measurement-based care, Behavioral health care, MBC websites

Acknowledgment

This achievement is a milestone in my academic and career. The journey started a long way and it was never meant to be easy. In the end, it is well that ends.

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List of abbreviations and Acronyms

2D	Two-Dimension(al)
ASM	Automated self-management
BH	Behavioral Health
BHC	Behavioral Health Care
CACT	Carnitine-acylcarnitine translocase
CBT	Cognitive behavioral therapy
CCBT	Computerized cognitive behavioral therapy
CDC	Centers For Disease Control
EBC	Evidence-Based Care
EHR	Electronic Health Records
FDA	Food and Drug Administration
FIT	Feedback Informed Therapy
ICBT	Internet-Delivered Cognitive Behavioral Therapy
ISG	Internet support group
LDA	Latent Dirichlet Allocation
LSA	Latent Semantic Analysis
MAT	Medication-assisted treatment
MBC	Measurement-Based Care
MCLDA	Multiple-channel latent Dirichlet allocation
MH	Mental Health
NHS	National Health Services
NLP	Natural Language Processing
NLTK	Natural Language Toolkit
NNMF	Non-Negative Matrix factorization
NQF	National Quality Forum

ORS	Outcome Rating Scale
PHQ	Patient Health Questionnaire
PLSA	Probabilistic Latent Semantic Analysis
PROM	Patient-Reported Outcome Measures
PROMIS	Patient-Reported Outcomes Measurement Information System
PTSD	Post-traumatic stress disorder
ROM	Routine Outcome Monitoring
SME	Subject Matter Expert
SMS	Short Messages
SNA	Social Network Analysis
SUD	Substance Use Disorders
TJC	The Joint Commission
UK	United Kingdom
URAC	Utilization Review Accreditation Commission
US	United States
VA	Veteran Affairs
VBC	Value-Based Care
WHO	World Health Organization

1 Introduction

1.1 State of mental health in the US

According to Mental Health America, more that 50 million adults in the US reported a mental health concern in 2022. This is about 20% of the adult population in the country. (Reinert et al., n.d.).

On the global scene, WHO (2015) highlights mental disorders as one of Europe's top public health challenges, affecting about 25% of the population annually. The covid-19 epidemic and increased social media use are making the situation worse. Therefore, traditional BHC interventions cannot cope with the growing mental health disorder burden. Some BHC providers, like the VA Department in the US, have fully integrated MBC in their BHC interventions supported by national policy changes. The lack of national and MBC provider support in the form of educational materials for clinicians, volunteer engagement, and not providing brief coaching for MBC implementation partially explains the low adoption of digital mobile technologies in BHC interventions. Also, BHC providers may not use full-package, complex MBC digital applications due to the burden associated with training, negative attitudes toward manuals or protocols, and beliefs that these technologies may not be appropriate for clients in the settings in which they practice (Simons et al., 2013).

1.2 Current state of MBC in the US

For a long time in medicine, a variety of methods and techniques of measurement have been used to monitor patients' responses to treatment and to inform adjustment decisions. For example, the Glycated hemoglobin test (HbA1c) has been used in diabetic and hypertension cases since 1958, while laboratory tests are routinely used for body liver function tests, cholesterol monitoring, or respiration (Sherwani et al., 2016). MBC is a systematic, ongoing assessment to monitor treatment progress and inform clinical decision-making (Jensen-Doss et al., 2020). MBC is considered an evidence-based practice, with extensive research support in adult clinical populations and emerging evidence in youth populations. With advancements in technology, there is potential for digital and mobile technology to augment the BHC in order to enhance accessibility, scalability, operational effectiveness, and clinical outcomes.

The MBC technology landscape has been changing over time. The initial effort was to determine and quantify measures that relate to patient experience. Today, several quantified PROM frameworks, guidance, and standards, e.g., NQF by FDA, PROMIS, and COSMIN, have been implemented as a minimum set of functionalities in most digital MBCs.

The next stage was the introduction of automation in the process. Automation helps monitor real-time patients' data in real-world environments and assists BHC Providers in identifying improvements and stressors to refine treatment plans. Digital MBC, for example, Mirah Inc's intuitive platform, now seamlessly integrates with any EHR system to receive the necessary patients' data, including appointments, providers, organizations, and other information.

In addition, mobile measurement-based care interventions present a perfect opportunity for BHC providers to reduce the treatment gap for (PTSD), depression, addictive behaviors, and anxiety disorders by overcoming some barriers to face-to-face therapy in older adults (Pywell et al., 2020). Moreover, as a framework to guide treatment, the uptake of mobile digital MBC applications by BHC providers to reach larger populations remains low (Vogel et al., 2017).

There is the potential for digital and mobile health technology to support numerous aspects of BHC if BHC can adopt MBC more effectively with the help of mobile applications and web-based platforms. Unlike traditional care, mobile based MBC offers real-time assessment of symptoms, functioning and life satisfaction, acknowledged processes of change, and treatment process, which may result in rapid case management and improved treatment outcomes. . Behavioral health clinicians will continue to suffer heavy caseloads and long hours of decision-making if they fail to integrate technology into behavioral health interventions (Larney et al., 2017). Similarly, (King et al., 2017) acknowledge the availability, reliability, and validity of patient-reported outcome measures for mental health, but their use to guide treatment is relatively infrequent. MBC providers are also likely not doing enough to support BHC providers in implementing MBC.

Regulators in the US are beginning to incorporate MBC into the standard practice of BHC Providers. TJC, as well as the URAC, are leading in this effort. However, due to the fragmented structure and organization of the healthcare system (TJC and URAC do not have a monopoly over jurisdiction and are not recognized in some states), it is challenging to implement MBC standards uniformly across the country.

1.3 Statement of the problem

The plethora of products and services in the digital marketplace has created significant development in the MBC arena. MBC, the systematic collection of patient-reported measures to monitor treatment progress and inform clinical decision-making, provides a platform for creating patient outcome measurement tools applicable in many areas of patient care (Ranallo et al., 2016). MBC outperforms usual care, with significantly improved outcomes for patients receiving mental health treatment; furthermore, studies show that MBC has the potential to improve PROM (Lewis et al., 2019), (Fortney et al., 2015) and (Washburn, 2022).

CDC data identify behavioral health issues like mental illness as among the most common health conditions in the United States (Centers for Disease Control, n.d.). About 20 percent of Americans will experience a mental illness each year, yet 4 percent of Americans live with a severe mental illness, such as schizophrenia, bipolar disorder, or major depression (Centers for Disease Control, n.d.)

Despite the documented efficacy of MBC in mental health treatment, research shows that its application to behavioral health care has been slow, limiting the extent to which consumers seeking care for mental health or SUD can derive its benefits. It is estimated that 89% of psychologists and 82% of psychiatrists in the US use clinical judgment alone and therefore fail to detect a lack of improvement or a worsening of symptoms in their patients (J. Fortney et al., n.d.).

Research conducted to identify the causes of the phenomenon (Lavallee et al., 2020) has drawn respondents from BHC or general medical practices leaving out other stakeholders such as MBC Technology Providers and Insurance Companies.

This thesis aims to provide insights, from the MBC Technology Providers dimension, into MBC implementation, BHC support, and other topics using Topic Modeling.

1.4 Research questions

The thesis will help answer the following research questions:

1. How can text mining be applied to identify topics discussed by MBC providers in a world where MBC can transform BHC?

2. What thematic topics are discussed by MBC service providers in shaping MBC within BHC?

2 Literature review

The section reviews the theoretical and empirical support for MBC application in BHC, including approaches to support BHC practices in implementing MBC, how MBCs improve patient outcomes, and the other topics being discussed by MBC providers in the context of the successful integration of MBC in BHC. Further, in this section, we survey the methods and techniques of data analysis as they relate to the work in analyzing data.

2.1 MBC providers focusing on how to support BHC practices in implementing MBC

Research evaluating MBC implementation is relatively new (Lewis et al., (2019) , but proposed strategies to address these challenges mirror those for quality improvement generally: training; local champions; careful selection of measures (e.g., engaging patients and practitioners in the selection of measures to ensure buy-in and relevance); routine use of clinic-based supervision and feedback.

A study by Lewis et al. (2019) (Harris et al., 2019) suggests that to increase the uptake and integration of MBC in BHC settings, MBC technology providers need to give training to clinicians, improve expert consultation with clinical staff, use measurement feedback systems, and generate incentives. The objective is to demystify BHC practitioner beliefs that MBC applications are no better than clinical judgment (Harris et al., 2019). Trust is also cited as a critical limitation to the uptake of mobile-based mental health interventions. Increasing training and awareness can boost BHC providers' confidence in integrating technology in their settings for real-time assessments and treatment. In some cases, BHC providers require approval or recommendation from trusted sources like the NHS (Gulliver et al., 2010).

According to Lewis et al. (2019) (Harris et al., 2019), MBC providers should develop algorithms for MBC to guide psychotherapy, harmonize terminology, and describe MBC's basic components in order to promote the integration of MBC in mental health clinical practice. create potential test mechanisms of change, notably for psychotherapy; establish criteria-based methods for fidelity monitoring and reporting quality of implementation; simplify measurement feedback systems to just include essential components and improve the interoperability of electronic health records; create concise, robust psychometric assessments that can be combined; evaluate the crucial administration timing required to maximize patient outcomes; identify specific implementation support measures; make decisions on policy based on factsstructures which Martin-Cook et al. (2021) believe demands a large investment of time, effort, money, and leadership.

Some BMC providers are encouraging physicians to engage a digital health coach to increase behavioral health care's implementation of digital and mobile health technology (Ben-Zeev et al., 2015). Adding a digital health coach to clinical settings may help patients and physicians in accessing digital interventions; however, it may increase the expense of using digital technologies. Similarly, (Moon et al. (2022) believe that digital and mobile health technologies may incur additional costs for providers due to the need for investment in the technology and its deployment. From this point of view, fairly affordable interventions like SMS text messaging may be recommended.

For doctors recommending mental health apps to patients, the American Psychiatric Association has developed an app-rating methodology (Raney et al., 2017). (Marshall et al., 2020). When determining whether an app is appropriate, physicians must consider four important factors: potential risk and harm, including privacy and data management; research evidence for efficacy; convenience of use; and the capacity to exchange data with clinicians if necessary. The approach does not take into account prior evaluations provided by other people, thus the clinician must "grade" the app from from scratch. It is difficult to picture practitioners in primary care or private practice settings frequently going through this time-consuming process, even though it may have future benefits for researchers. Additionally, although believing that the issue of efficacy is important, the app does not offer a measure of efficacy (Marshall et al., 2020).

According to Sinclair et al. (2013), mental health professionals who have been trained in the scientist-practitioner model of evidence-based practice may be reluctant to utilize or even suggest mental health applications. This is due to the fact that many applications have not been shown to be helpful and can include interventions or information that is not supported by evidence (Kertz et al., 2017). Increasing the evidence base of mental health apps may increase the likelihood that clinicians recommend them to patients, which may increase the adoption of mental health apps given that consumers of mental health services are frequently receptive to recommendations from their treatment providers (Pung et al., 2018). (Neary & Schueller, 2018). Clinical professionals will only use computerized virtual systems to recommend an antidepressant more frequently after this happens (Marshall et al., 2020).

The Head to Health website (https://headtohealth.gov.au/), which offers information about digital mental health choices to both consumers and physicians, was recently established by the Australian Federal Government. Similar recommendations and reviews can be found on reachout.com, an

Australian non-profit organization, at https://au.reachout.com/tools-and-apps. Additionally, the Australian National University contributed funds to the creation of the beacon website (https://beacon.anu.edu.au), which provides rated digital mental health resources (Marshall et al., 2020).

The Health Navigator website (www.healthnavigator.org.nz) was initially developed in New Zealand to help general practitioners locate information on a variety of health problems, including mental health. However, it can be used by consumers and doctors to find information on digital mental health initiatives, websites, and applications. It makes these materials available to a larger community and contains connections to various resources that individual District Health Boards may have developed. The New Zealand Health App Library is located on the Health Navigator website and offers summaries of information on apps for mental and general health, as well as reviews of these apps from consumers, general practitioners, consumers, and application development experts. Even while the websites for Health Navigator, Beacon, Reach Out, and Head to Health admit numerous challenges in recommending mental health apps, each one follows a clear procedure. Once more, they do not offer scientific proof of any app's effectiveness, but they do acknowledge any prior research that may have been done on the app (Marshall et al., 2020).

Despite available evidence that MBC improves the quality of care and clinical outcomes (Fortney et al., 2017; Guo et al., 2015; Scott & Lewis, 2015), integration of MBC in BHC still needs to be improved across the US. Based on the Kennedy Forum data, only 18% of psychiatrists and 11% of psychologists in the US routinely administer symptom rating scales to monitor treatment response (Jones, 2022). Hence MBC providers have an uphill task of helping BHC practitioners implement the innovation. However, concerns about the potential administrative burden of MBC, fear of accountability, and ordinary human foible probably drive the lack of uptake (Fortney et al., 2017).

During the process of incorporating MBC into the general Psychiatric Outpatient Clinic at the University of Texas in Dallas, significant obstacles arose. Among the key obstacles was the rapid realization that fundamental metrics could not meet the requirements of specific patient populations. Our addiction team required measures relevant to relapse prevention, issues of standardization and questionnaire fatigue, difficulties on how to best share results with patients graphically during telehealth encounters, and concerns on how to most effectively manage patients who continuously report high scores (Martin-Cook et al., 2021). Despite the fact that MBC was effectively integrated with the Clinic, the aforementioned obstacles explain why the innovation has not yet been broadly introduced into normal behavioral health treatment in the United States. It is also feasible that MBC providers will need to assist BHC practitioners with the innovation's implementation.

Although many critical barriers to MBC implementation are well known, developing and testing research and practice-informed strategies to address such barriers have yet to catch up. Notably, however, there is growing recognition that implementation science methods and principles can begin to address some of these critical barriers (Childs & Connors, 2021; Lewis et al., 2019). While still nascent, the growing field of implementation science and increasing literature on the integration of routine, standardized patient assessment in other specialties offer a starting point for effective implementation planning (Chan et al., 2019; Gerhardt et al., 2018; Nelson et al., 2020; Sisodia et al., 2020). Therefore, MBC providers must increase collaboration with BHC practitioners to develop strategies to mitigate patient, provider, and system-level barriers.

2.2 How MBCs improve patient outcomes

Web or mobile-based mental health programs are effective for both adults and children in reducing anxiety and depression symptoms (e.g., Ebert et al., 2015; Richards & Richardson, 2012). There is now an interest in how standalone e-mental health programs (i.e., programs that can be downloaded once and do not need an ongoing Internet connection or regular therapist involvement) further enhance the clinicians' digital toolbox. Some studies have compared the effectiveness of e-mental health programs with face-to-face therapy and have found comparable (e.g., Andrews et al., 2010; Richardson et al., 2010) and, in some cases, even more favorable results (e.g., Merry et al., 2012). However, one of the main differences in results between e-mental health programs and face-to-face therapy is that participant drop-out rates appear to be significantly higher for computerized conditions (Andrews et al., 2010; Richardson et al., 2010), and this issue requires further research (Engel et al., 2016) (Marshall et al., 2020). The study was based on a randomized trial comparing CACT with usual integrated mental health care for PTSD or depression. Patients, primarily men in their 20s, were enrolled in 18 primary care clinics at six military installations from February 2012 to August 2013, with a 12-month follow-up completed in October 2014 . Another study (Wu et al., 2018) revealed that technology-facilitated care and supported care delivery models could improve 6-month depression and functional disability outcomes. Technology care model is more likely to succeed in improving patient statist faction depression, and diabetes .

There is no evidence to support the concept of online collaborative care in the treatment of anxiety and other disorders. (Bruce et al. (2018. Lewis et al. (2019a) conducted a comparative analysis of ASM effectiveness vs. ASM-enhanced collaborative care in another randomized clinical trial. The findings revealed that the two intervention models are heavily reliant on telecare delivery but, with varying resource and intensity, produced moderate improvements in pain and mood symptoms. The model that combined collaborative care led by a nurse-physician team with web-based self-management, on the other hand, outperformed self-management alone (Kroenke et al., 2019).

2.3 Latent Dirichlet Allocation

LDA methodology (Blei et al., 2003) explores and identifies topics within the web content. In this study, we use the LDA methodology to analyze a large amount of data. We choose LDA because of the nature of the research, which is exploratory significant growth as a topic modeling method within academic research, business analytics, machine learning, and general online text analysis (Asmussen & Møller, 2019; Jelodar et al., 2019). LDA modeling and analyses on academic literature have been done in research areas as diverse as Information Sciences (He et al. 2013), Accounting (Fang et al., 2018), Computational Linguistics (Hall et al., 2008), Biology (Zheng et al., 2006), and Business & Economics (Piepenbrink and Nurmammadov 2015). In most studies of this type, the work was done in an exploratory manner in search of the underlying topics being discussed. However, LDA-related studies have also been conducted for side-by-side comparisons with pre-existing manual coding schemes (Nelson et al., 2021) or conducted as the input to a different manual categorization exercise using the LDA model topics (Grimmer & Stewart, 2013). LDA is widely used and accepted, as noted by the substantial citation count (nearly 40,000 on Google Scholar as of Sep 2021) associated with the original paper that introduced the LDA methodology (Blei et al., 2003).

Given the extensive use of LDA in past studies, we now describe the methodology and underlying model structure. LDA disregards the sequence in which words occur and syntactic information, only treating documents as a collection of words, more commonly known as a "bag of words". The basic premise underlying LDA is that a document comprises a mixture of topics, and each is a mixture of words (Blei 2012) . By finding the words in a topic, we can then use those words to identify the topics in a document. Breaking down LDA into its component words (Sharma, 2022), the assumption is that there is a "Latent" or hidden distribution of topics within a corpus of documents. These hidden distributions are composed of "Dirichlet" distributions for the distribution of words to topics and topics to documents. Finally, the "Allocation" signifies that the topics are allocated across the documents, meaning each document is likely to have multiple topics covered within it. The general graphical structure of LDA is shown in Figure 2-1 (Blei 2012). Documents are assumed to be composed of a random assortment of topics, and topics have a probability distribution over words (Wayesa Gemeda, 2019). Each box (plate) in Figure 2-1 represents the sampling steps needed to achieve the number of samples in the lower right corner of the box (D = documents, N = words in a document, and K = topics). The term a can be thought of as the prior observation count (latent count) for the times a topic is sampled in a document. The term n can be thought of as the prior observation count (latent count) of the number of times words are sampled before any word from the corpus is observed. More specifically, LDA assumes that documents are generated from the probabilistic processes as follows (Blei et al., 2012).

For each topic *k,* draw from topic distribution~ *Dirichlet(n'),h &* {1,..., *K*}
For each document *d,* draw topic proportions from *0 ~ Dirichlet(a)*
For each word *n* in each document d,
Draw a topic assignment from the topic proportions *z,\0 ~ Multinomial(0)*
Draw the word from the corresponding topic, *w,\z,, 0 ~ Multinomial(ft,)*

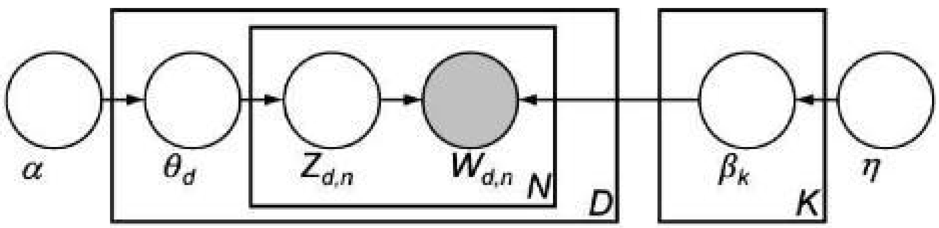


Figure 2- 1: Probabilistic graph model of Latent Dirichlet Allocation (Blei, 2012)

LDA has been used in modeling healthcare data. In their study, proposed using a novel multiple-channel latent Dirichlet allocation (MCLDA) for healthcare providers to understand big healthcare data better and to develop better data-driven clinical decision support systems (Lu et al., 2016). The authors argue that MCLDA can help healthcare providers to handle diagnoses, medications, and contextual information effectively. The model also makes it easier to discover patient groups and corresponding characteristics, predict diagnoses by giving medications and vice versa, pair diagnoses and medications in a record, and evaluations based on millions of health records (Lu et al., 2016) . However, the model was proposed for healthcare providers in general and not specifically for BHC providers.

Lunn et al. (2020) combined SNA and LDA methods to discover common shared topic keywords to understand better the underlying behaviors of physicians and nurses in different harm-level medical adverse events. The main objective was to improve the process—a total of 17,868 medical adverse event data records were collected between 2000 and 2017. The study revealed that communication, information transfer, and inattentiveness were the most common problems reported in the medical adverse events data. The research demonstrates that LDA is quite effective for gathering and making sense of vast amounts of health data records, making it worthy for BHC providers to implement (Blei et al., 2003).

2.4 Topic analysis using pyLDAVis

Various tools, such as pyLDAVis, have been proposed for guiding users through the interpretation of vast quantities of documents on various topics using visual analytics. pyLDAVis is a topic modeling exploration tool that provides a straightforward method for visualizing the most relevant words within each topic, their distribution across topics, and the relative distance between topics when reduced to a 2D space.

These tools display a wide range of clustering algorithms, validation indices, and user-facing visualizations, but only a handful can handle incomplete longitudinal data. Topic interpretation and analysis done by humans may fail to provide the correct information due to fatigue and stress associated with the process (Fang, 2017; Zhang et al., 2016), which can complicate the diagnosis and treatment of psychological disorders such as PTSD, anxiety, depression, eating disorders, and manic-depressive disorder.

In pyLDAvis visualization, each circle in Figure 2-2 represents a topic, and the circle's size represents the topic's frequency. The distance between the circles represents the similarity between the topics. The further they are, the more independent; some topics are relatively close to each other, even overlapping, indicating that there is a highly similar between them. From the results of pyLDAvis visualization, it is necessary to minimize overlap between topics. The appropriate number of topics and the distribution between the various topics should be reasonable (Xu et al., 2020)

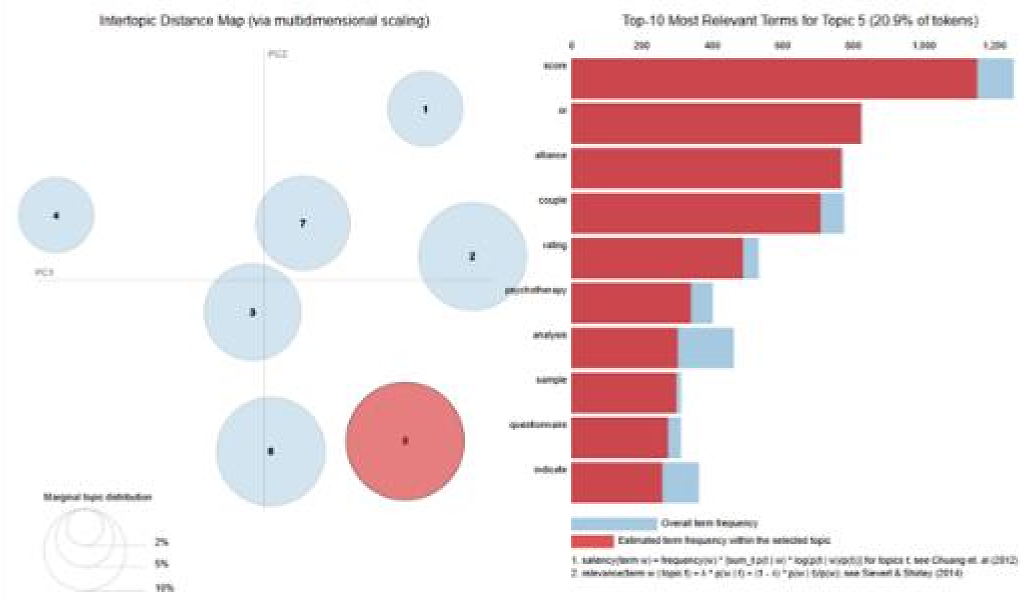


Figure 2- 2: Sample pyLDAVis chart

Lately, focus is shifting to visualizing the output of topic model fit using LDA (Gardner et al., 2010; Chaney & Blei, 2012). With the aid of modeling exploration tools such as pyLDAvis, BHC can analyze thousands of documents relating to specific patient conditions and develop the most effective interventions. However, creating such representations is complex due to the high dimensionality of the fitted model. LDA is applied to a large number of documents, consisting of many themes, and the themes themselves are a mixture of many words (Sievert & Shirley, 2014)

While many visualization systems for topic models have been developed recently, more needs to be done to assess their applicability in informing behavioral health care interventions. Several of these systems focus on enabling users to navigate documents, topics, and terms to discover the relationships (Gardner et al., 2010; Chaney & Blei, 2012; Snyder et al., 2013). These visualization capabilities are typically limited to bar charts, pie charts, and additional bar charts and scatterplots linked to document information. Although these tools can help browse a corpus, we seek a more compact visualization with a narrower focus on quickly and easily understanding specific topics.

Interpretation of topics using visualization models has been widely documented in the academic and natural work spheres.

BHC practitioners deal with various documents on varying topics. Finding answers to a few basic questions, such as the meaning of each topic, can be stressful and time-consuming. However, Gensim, an open-source library, can provide seamless topic modeling to inform personalized behavioral health care. There is abundant literature suggesting the application of Gensim in different disciplines, including medicine, patent search, and insurance. However, the literature below is limited to the applicability of the Gensim tool in topic modeling by behavioral health care practitioners.

Topic modeling has shown promising results for behavioral health issues detection. Resnik et al. (2015) demonstrated that topic models such as LDA could uncover meaningful and promising latent structures within depression-related language collected from Twitter. Coppersmith et al. (2015) confirmed the potential of using social media content, such as Twitter posts, for depression and PTSD binary classification. In addition, Zhao et al. (2011) showed the potential of using Twitter content for topic extraction, and Jelodar et al. (2019) reiterate topic modeling and LDA capacities to uncover hidden structures related to user behavior in social media. Although previous work demonstrates the effectiveness of topic modeling for depressive-related conditions, there needs to be a more horizontal application of this approach to various mental health issues to compare them and assess their potential on a case-by-case basis. Furthermore, combining corpus concerning different mental health issues to perform such an approach is untested analyzed how pyLDAvis facilitates visualizing and interpreting topics. Although the researchers emphasize the applicability of pyLDAvis in visualizing and interpreting topics, their analysis is not specific to MBC in behavioral health, which is the purpose of the current research. The authors provide a global view and deep inspection of the terms most highly associated with each topic, including the choice of terms for topic interpretation, presentation of results a visualization system (Sievert & Shirley, 2014).

2.5 Web scraping

The web is both a data depository and a data source. Individuals and groups of people add data to the web through postings on websites, social media, etc. Likewise, end users can extract this data where access is granted for research, academic, and other purposes. Data on the internet is in significant volumes, constantly changing, and takes on many forms (structured, unstructured, and semi-structured).

To collect data from the internet, users apply techniques such as web scraping and web crawling. Web scraping and web crawling are used interchangeably during data extraction; they perform different tasks (Massimino, 2016; Muehlethaler & Albert, 2021; Vanden Broucke & Baesens, 2018).

A web crawleris a web application that systematically scans the internet intending to collect multiple URLs (Parvez et al., 2018). Web crawling comes in handy in cases requiring extracting data from multiple websites simultaneously (Massimino, 2016).

Web scraping is extracting existing information from the web (Arifanto et al., 2018; Fatmasari et al., 2018; Katre, 2019; Lunn et al., 2020) . Copy and paste is the most straightforward web scraping technique but can be tedious and require many resources for big data. To be efficient, individuals and companies can leverage existing scraping algorithms, web extensions, plugins, and software platforms (Diouf et al., 2019). Web scraping is utilized in text mining and NLP in sectors; of health, education, politics, meteorology, communication, entertainment, transportation, etc. (Arifanto et al., 2018; Diouf et al., 2019; Fatmasari et al., 2018; Katre, 2019; Lunn et al., 2020) . According to (Arifanto et al., 2018) , some challenges faced during the web scraping process are diverse data types, structures, and information.

Many web scawlers are implemented using the Python programming because Python is simple and easy to learn and to implement. In addition, Python has a large base of community support (Khder, 2021).

3 Model Development

Our model is developed using a process outlined in the flowchart shown in Figure 3-1. The phases are business and data understanding, data preparation, modeling and evaluation, and deployment.

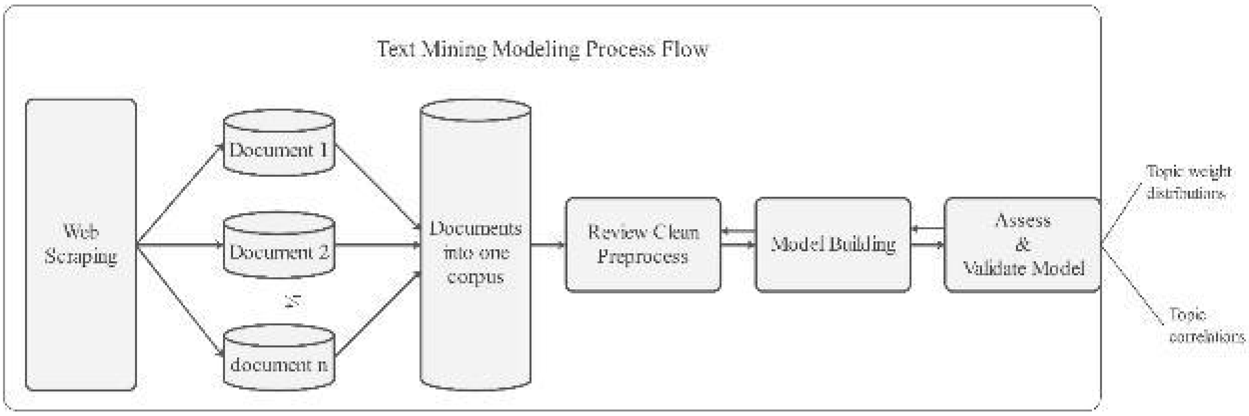


Figure 3- 1: Text mining process flow

Step one is data collection which involves identifying relevant MBC provider companies and their websites and conducting a web scraping exercise to obtain documents that will be used to create a corpus for our research. The next stage is Data Preparation which involves data cleaning and reformatting. The third stage is Model development. This stage involves two processes: the first one is using LDA to identify topics, and the second one is naming, with the help of SMEs (in this case, the Clinicians), the topics. Stage four, the Analysis stage, involves exploring the identified topic interactions and company similarities.

3.1 Research model and methodology

This thesis relies on textual data from MBC Providers' websites using web scraping tools. With such textual data, we need text mining techniques that effectively discover relationships in the collected data and correlate them among data and text documents. While many options are available, each with varying success and complexity, the thesis uses LDA to explore and identify topics.

To obtain the required data from the different websites, we use web scraping techniques provided by Python. Web scraping can be done using either Beautiful Soup or Selenium. While both are adequate for the task, we choose to use Beautiful soup because of ease of use and because the content was not dynamic.

3.2 Data sources

Many MBC Providers post relevant data on their websites. Such data can be analyzed to provide thematic patterns and important lessons extracted. Data will be collected using Web scraping and web crawling techniques. These are tested techniques that provide reliable results and are considered legitimate tools in data analysis (Han-Wei Liu, 2020 &Trivedi et al., n.d.).

Because data will be collected from publicly available sources (i.e., company websites), issues of the confidentiality agreement will not arise. Proprietary data, where companies explicitly require permission to use the website data, will be excluded from the research (Krotov, 2018).

3.3 Data collection

3.3.1 Selection criterion

To guide the selection of websites to be included in the study, we conduct an initial phase of the company search employing best practices (Okoli, 2015). The first step is identifying and refining the appropriate search criteria to evaluate across as many target companies as possible. The search specifies MBC companies in the US and documents that are written in the English language. The language requirement is to avoid loss of value during translation and to minimize interpretability issues. We conduct our search using the Google search engine to identify companies meeting the search criteria. Table 3-1 shows the search criteria we apply.

Criteria 1	Description
Search engine	Google
Language Translation	English
Companies searched	MBC companies
Company locations	US only
Document Type	Blog, Case study, Testimony, Company, Product Info, News, Press Releases, Announcement, Research, Webinar, and Podcast
Text captured	Title and text associated with the document type
Document format	Web pages and PDFs
Boolean keyword	MBC, VBC, and EBC in BHC

Table 3- 1: Criteria for identifying websites for web scraping

The search criterion in Table 3-1 excludes companies that integrate MBC into their solutions (even when they are not solely MBC providers) and companies with a presence outside the US. To broaden the scope, we revise the criterion to include additional terms (such as PROM, ROM, FIT, outcome measurement and systematic client feedback in BHC, and psychometrics) and companies with a presence outside the US. The revised criterion is shown in Table 3-2.

Criteria 2	Description
Search engine	Google
Language Translation	English
Companies searched	MBC providers (including MBC, HER, and other companies)
Company locations	US, Canada, UK, China, Switzerland, Malaysia, Ireland, etc.
Document Type	Blog, Case study, Testimony, Company, Product Info, News, Press Releases, Announcement, Research, Webinar, and Podcast
Text captured	Title and text associated with the document type
Document format	Web pages and PDFs
Boolean keyword	MBC, VBC, EBC, PROM, ROM, FIT, outcome measurement and systematic client feedback in BHC, and psychometrics

Table 3- 2: Revised criteria for identifying websites for web scraping

The search using criterion 2 results in companies shown in Table 3-3

Provider	Country	Website
Azzly	US	https://azzly.com/
Better Outcomes Now	US	https://betteroutcomesnow.com/
Bhworks	US	https://mdlogix.com/
Blueprint Health	US	https://www.blueprint-health.com/
Celesthealth Solutions	US	https://www.celesthealth.com/index.asp
Greenspace Health	US, Canada	https://www.greenspacehealth.com/en-ca/
Holmusk	US, UK, China, Switzerland, Malaysia	https://www.holmusk.com/
Horizon Health	US	https://horizonhealth.com/
Ksana Health	US	https://ksanahealth.com/
M3 Information	US	https://www.m3information.com/
Mirah Inc	US	https://www.mirah.com/
MyOutcomes	US, UK, 26 Other countries	https://www.myoutcomes.com/
NeuroBlu	US	https://www.neuroblu.ai/
Neuroflow	US	https://www.neuroflow.com/
Next steps Solutions	US	https://www.nssbehavioralhealth.com/
NView	US	https://nview.com/
OQ Measures	US	https://www.oqmeasures.com/
Owl Health	US	https://www.owl.health/
SilverCloud	US, UK, Ireland	https://www.silvercloudhealth.com/uk
Tridiuum	US	https://tridiuum.com/
Valant	US	https://www.valant.io/
ViviHealth	US	https://www.vivihealth.com/

Table 3- 3: MBC providers, their locations, and domains

3.3.2 Collection methodology

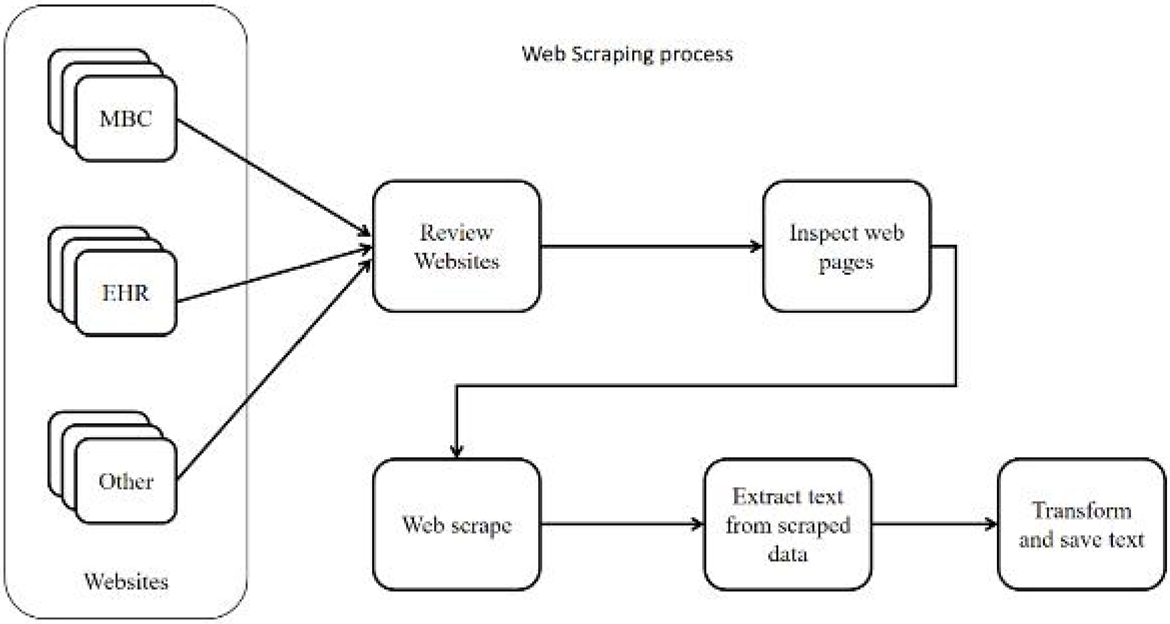


Figure 3- 2: Web scraping workflow

We use web scraping techniques to collect textual data from the websites of MBC Providers. Such techniques provide reliable results and are considered legitimate tools in data analysis. (Han-Wei Liu, 2020), (Trivedi et al., n.d.).

Since websites have vast data, we first navigate through each website to see how they are structured. We notice that some websites have static web pages (whose content does not frequently change unless the developer updates) while others have dynamic pages (whose content changes frequently). Requests and Beautiful soup are good candidates for scraping static websites but can be challenging for dynamic websites. For dynamic websites, selenium is more effective (Uppal & Chopra, 2012). Python uses the Requests and Beautiful Soup libraries to send requests to access HTTP data using the requests.get() method and fetch data from an HTML or XML format with the BeautifulSoup() function, respectively.

We inspect each page to understand the structure of the content we want to harvest for the analysis. We hover over the text to see which element or tag it belongs to, e.g., div, span, article, section, or header, and the corresponding class where it is contained. We use requests to scrap HTML code from the selected websites and beautiful soup to get the data elements and classes as they are on the website.

Some websites have web pages contained in other web pages. To navigate this issue of nested pages, we develop a looping script to parse the pages to mine the nested links. The scraper is set to run every 3-10 seconds to avoid overloading provider websites. We can then retrieve the desired content from the different websites by defining parameters for; tags, classes, IDs', attributes, etc., depending on the page structure.

We specifically scrape page titles and the corresponding descriptions of the web pages. The text is included in our analysis, and the title reflects the perspective on the discussed topics. We include the following in our corpus: case studies, testimonies, news, press releases, announcements, blogs, research articles, white papers, podcasts, webinars, about us, team, who we are, who we serve, product features, solutions, use cases, and frequently asked questions (FAQs) to our corpus. These are in the form of either web pages or Portable Document Formats (PDFs). To scrape PDF content, we use pdfminer to extract the documents from the web and PyPDF2 to transform the pages of the pdf files.

Finally, we convert the data into utf-8 encoding and save the output as a .txt file under the respective company folders for easy profiling during manual data preparation.

3.4 Data preparation

The process involves three fundamental processes, namely manual data preparation, word list creation, and word list cleaning, as shown in Figure 3-3

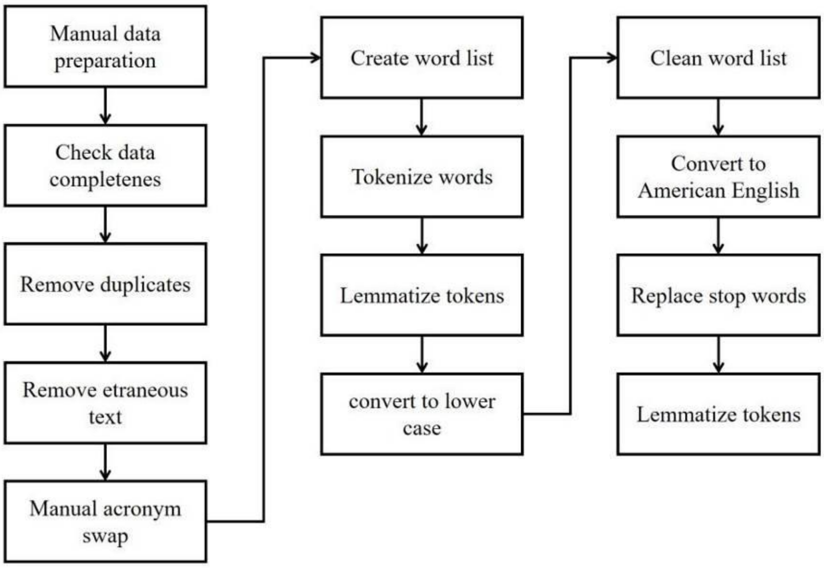


Figure 3- 3: Data pre-processing workflow

3.4.1 Manual data preparation

Web scraping content contains emojis, punctuation marks, hypertext, email addresses, headings, footers, e.t.c, which add noise to the data. They contain items that affect the data quality but will not be helpful in the proceeding stages of the analysis and need to be removed.

Data cleaning is needed to check the data for any inconsistency, quality, or other issues that could be problematic (Chu et al., 2016) . We eliminate documents with non-English translation (specifically from companies outside the US) and documents from Providers of MBC in areas of health care other than BHC. This review removes several hundred non-English translations and non BHC-related documents. We then eliminate types of entries that skew data language. We visually inspect and remove header text, footer text, hyperlinks, tables, references, embedded images, and email addresses.

We check to ensure that acronyms are consistently used within the documents; when this is confirmed, we retain the acronyms. In an instance, the acronym ORS, which translates to "Outcome

Rating Scale", is modified to "or" during the data pre-processing stage and keeps showing up at the visualization stage. In such circumstances, we examine the word to see whether it adds value and convert it to the complete form. Other items that need to be removed include numeric digits, hyperlinks, email addresses, computer non-printable characters, e.t.c.

3.4.2 Creation of a word list

We construct a document term matrix (DTM) in typical topic modeling from input documents. A vocabulary-based document term matrix is created; we collect unique terms from all the documents and mark each with a unique id using the create vocabulary function. The first step to vectorizing text is creating a map from words to a vector space.

We convert text to be machine-readable for natural language processing (Ignatow & Mihalcea, 2017). The documents processed to this level are then subjected to a tokenizing process to split the document word level creating individual words (tokens) for further processing. For this stage, we use spaCy, a free, open-source library for advanced NLP in Python. spaCy API is available online at https://spacy.io (Vasiliev, 2020).

Next, we lemmatize the tokens, identifying appropriate punctuation like contractions and abbreviations in the text. We use spaCy to identify the part of speech of each word in a document and then tokenize that word using its proper base form using lemmatization. We only keep nouns, verbs, adverbs, adjectives, or proper nouns. Finally, as part of the lemmatization, all tokens are made lowercase to ensure the exact words would not be treated as two tokens due to different capitalizations. The output of this stage is a list of tokens representing each document.

Next, we swap words with British spelling with the equivalent American spelling. To achieve this task, we use the online dictionary of British-to-American translations at https://github.com/hyperreality/American-British-English-Translator (Hyperreality, 2016).

We then remove stopwords, which are high-frequency words such as pronouns (e.g., we, them), determiners (e.g., an, the), and prepositions (e.g., in, on, of) (Ignatow & Mihalcea, 2017) using the NLTK built-in stopword dictionary (Bird et al., 2009). In most cases, these words do not add value to the topics discussed (Resch et al., 2018). We then clean up the list of words for each document by removing words with one or two characters.

Finally, we rerun the lemmatization process one extra time. The reason for this is to remove proper nouns based on their part of speech and to account for any remaining transformation of words to their bases (e.g., any plurals remaining are turned into the singular form). Upon completing the pre-processing phase, our corpus consists of 13,348 distinct tokens across the 1,719 documents shown in Figure 3-4. The companies that provide the most documents are collected from SilverCloud Health, Valant, and Azzly. In contrast, Vivi Health, CelestHealth, OQ Measures, M3 Information, and Mirah provide less than 20 documents collected. More than 60% of our corpus contains blog data, with very little data from case studies, webinars, and podcasts.

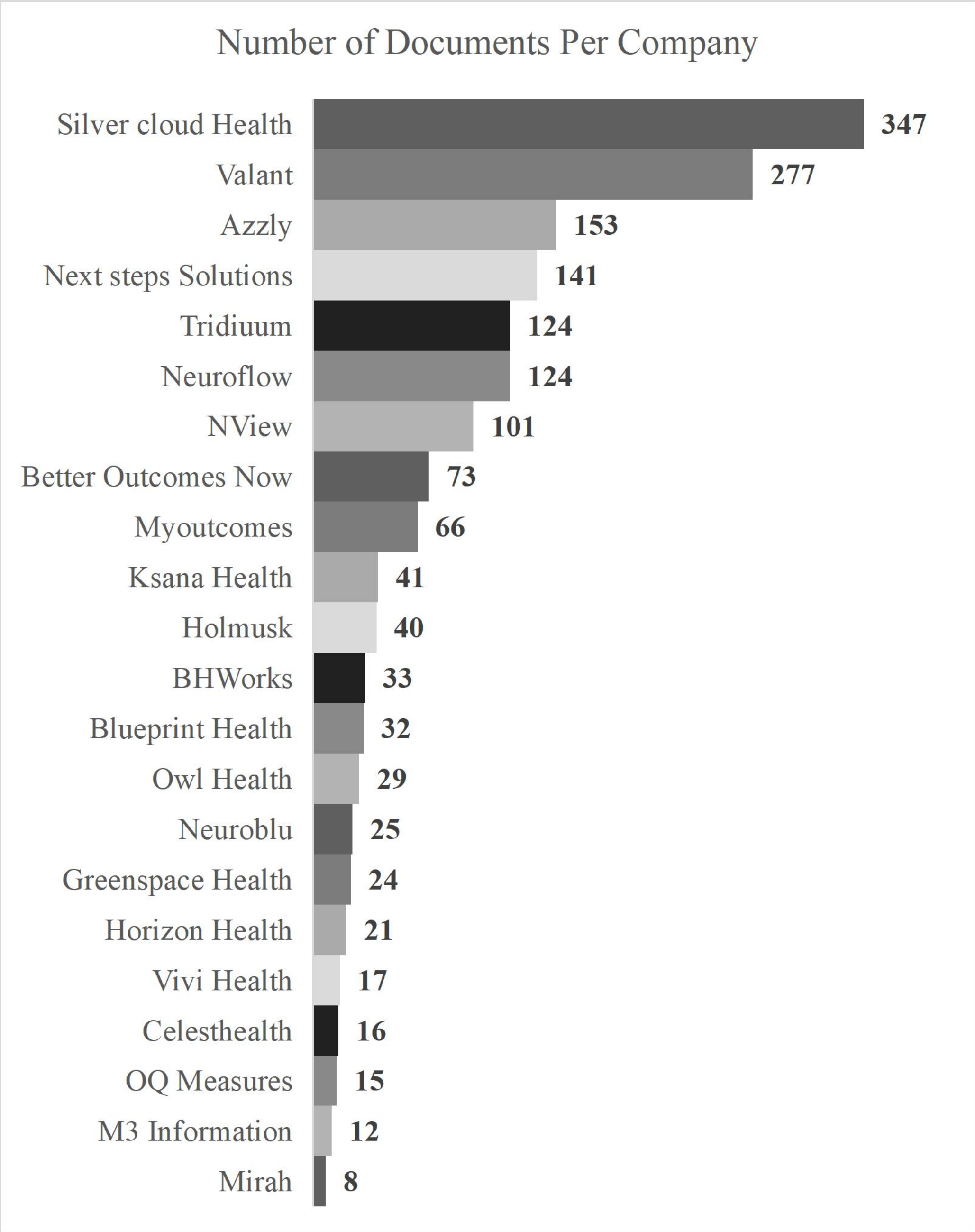


Figure 3- 4: Number of documents for each company

The graph in Figure 3-5 shows the composition of documents by type. Blog information makes up more than half of the total available documents.

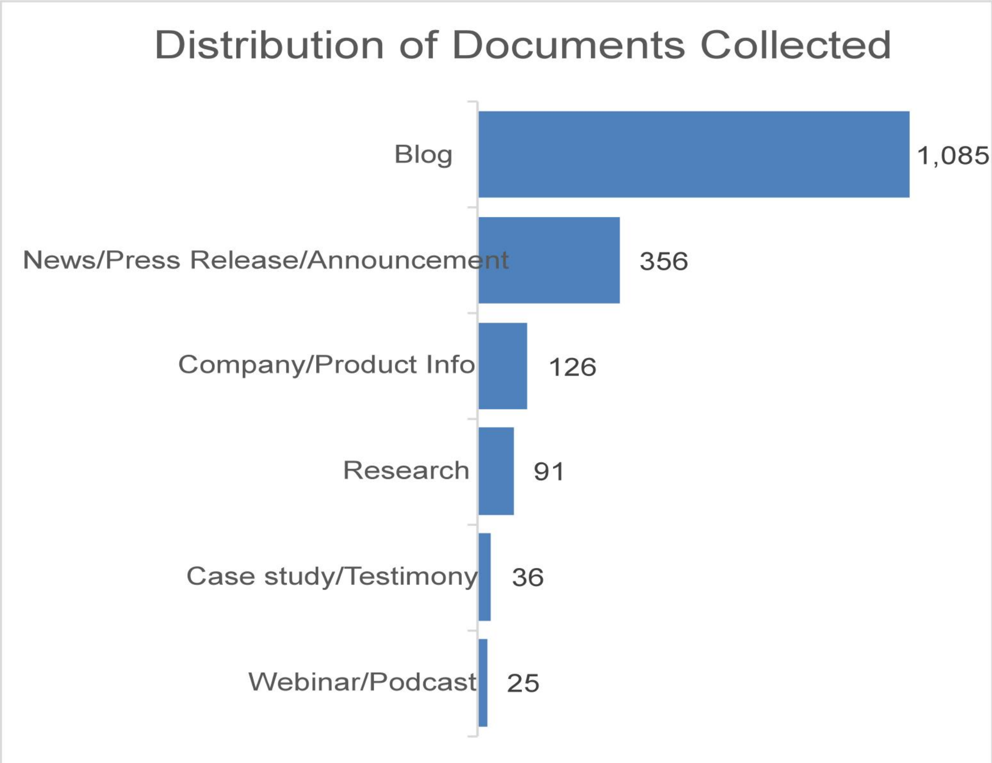


Figure 3- 5: Distribution of documents collected

3.5 LDA model development

We conduct a topic modeling analysis using the LDA technique (Blei et al., 2003) to identify topics and use the Python Gensim (version 4.1.2 with Python version 3.9.13).

Before initiating modeling, LDA requires the number of topics to be specified (Wayesa Gemeda, 2019). However, this number is not known as apriori, so scientific approaches need to be used to derive the number of topics. The statistical strategy for determining the appropriate number of topics is to Coherence and Perplexity to select the model with the lowest Perplexity. Although Perplexity can make the model's prediction ability the best, it tends to choose a more significant number of topics, which leads to a higher similarity between the selected topics, resulting in problems that are difficult to identify and affect the topic result of further analysis.

As a workaround for this constraint, estimation methods are used by iterating a range of values and deciding the optimal number using selection. The number is determined by running the model with a set of values. The results of the models are then plotted and analyzed using pyLDAvis visualization. pyLDAvis charts display circle sizes proportional to the frequency of the topic. The proximity of the circles reflects a high degree of coherence and vice versa. Where the circles are distant from each other, that signifies a lack of coherence. The objective of the variation is to minimize topic overlap.

3.5.1 Model parameters

The range of parameters needed for the model is shown in Table 3-4. We set the α and η values to "Auto" to let the Gensim model seek out automatically and converge on favourable settings as it runs through multiple iterations.

The LDA model requires the selection of settings and hyperparameters, as shown in Table 3-4. To determine the settings, we use Hoffman et al. (2010) recommendations to set the κ(kappa) to 0.5, τ(tau) to 64, and the batch size (S) to ≥ 256, respectively. We set the α and η values to "Auto" to let the Gensim model seek out automatically and converge on favorable settings as it runs through multiple iterations. Additional settings include the number of “passes” and “iterations” Gensim applies convergence the model (Hoffman, Bach, and Blei 2010). The “iterations” setting represents a maximum limit of how many times the algorithm may repeat each document’s probability distribution assignments, imposing an upper cap on how long the process will run if all documents have not achieved convergence. The setting “passes” is the number of times the algorithm trains the model on the entire corpus. To determine appropriate settings for passes and iterations, we ran multiple versions of the model process while recording every pass (i.e., “eval_every” = 1) to determine how quickly the model was converging. Finally, to enable comparison between runs, we choose a random seed (i.e., “random” = 42) to set a constant start point for model runs.

Parameter	Setting
κ	0.5
τ0	64
S	256
α	auto
η	auto
eval_every	1
passes	40
iterations	100
random	42

Table 3- 4: LDA model parameters

3.5.2 Creating a full range of models

We conduct Gensim model runs to identify candidate models while varying the parameters shown in Table 3-4. The first parameter we vary is the number of topics ranging from 10 to 30. The following two parameters we change are related to the pruning of frequently and infrequently used words (Grimmer and Stewart 2013; Maier et al. 2018). We provide the model with three cut-points for the frequently used words, removing words that appear in more than 15%, 20%, or 30% of the documents. Frequently used or ubiquitous words within the corpus will not help distinguish clear lines between the topics. We also use cut-points for words that appear in at most 5, 10, 15, or 20 documents for the infrequently used words. Infrequently used words appearing within only a tiny subset of documents will not help identify the discussion within the corpus.

Additionally, removing infrequent words also reduces the size and sparsity of the document-term matrix, thereby reducing overall model runtimes. When looking at all possible combinations of these parameters, there are 270 unique models we build with Gensim. Each model takes approximately 33-52 minutes to train and build with our established parameters in Table 3-5. To expedite the creation of the 270 models, we use a ldamulticore instance to create our models in parallel, saving all results for later analysis and assessment.

Parameter	Values	Combinations
No of Topics	10- 30	21
Frequent words	Words in no more than 15%, 20%, or 30% of documents	3
Infrequent words	Words in at least 5, 10, 15, or 20 documents	4
	Total combinations (21*3*4)	252

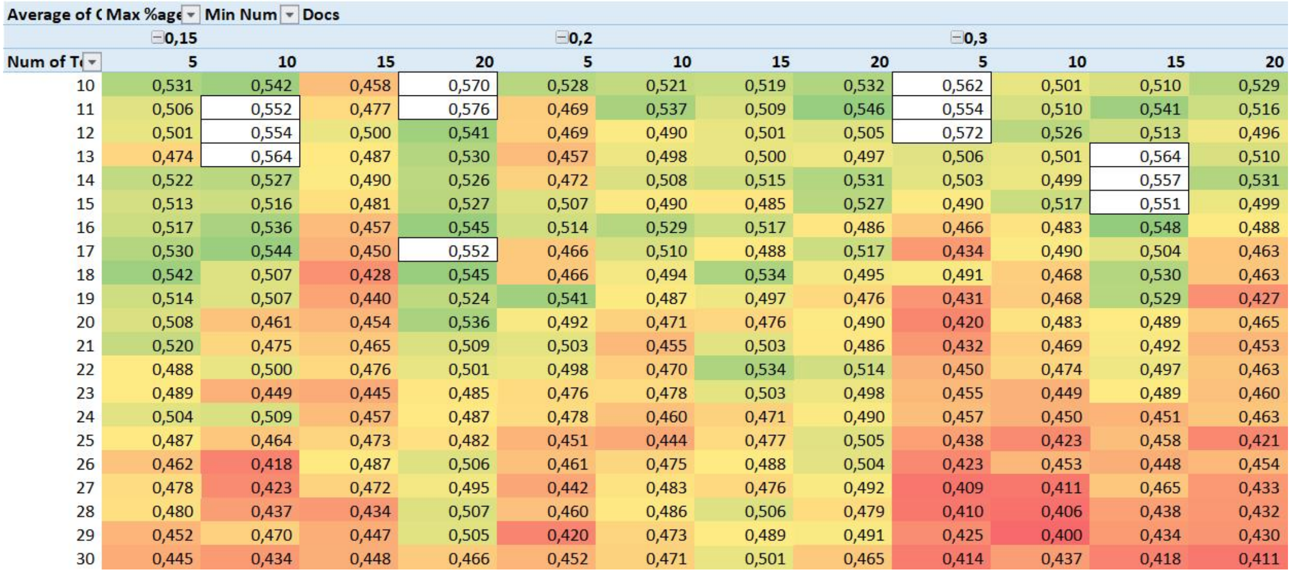
Table 3- 5: Parameters for running multiple models for assessment

3.5.3 Selection of models

3.5.4 Selecting the potential model using coherence and perplexity

Out of the 252 models, we select models with interpretable topics based on their Coherence and Perplexity scores. Coherence for each model is determined using the Genism Cv measure (Röder et al., 2015). High values of the Cv measure (Maximum 1.0) imply more interpretable topics and vice versa. Perplexity is a measure of model generalization (Hoffman et al., 2010).

Figure 3-6 is a heatmap showing the Coherence scores of all 252 models. To screen for representative models, we initially limit our review to models with the top 12 Coherence scores of 0.551 to 0.576. Models in that range are highlighted in white in Figure 3-6.



Average of C	Max %age / Min Num Docs											
	0,15				0,2				0,3			
Num of T	5	10	15	20	5	10	15	20	5	10	15	20
10	0,531	0,542	0,458	0,570	0,528	0,521	0,519	0,532	0,562	0,501	0,510	0,529
11	0,506	0,552	0,477	0,576	0,469	0,537	0,509	0,546	0,554	0,510	0,541	0,516
12	0,501	0,554	0,500	0,541	0,469	0,490	0,501	0,505	0,572	0,526	0,513	0,496
13	0,474	0,564	0,487	0,530	0,457	0,498	0,500	0,497	0,506	0,501	0,564	0,510
14	0,522	0,527	0,490	0,526	0,472	0,508	0,515	0,531	0,503	0,499	0,557	0,531
15	0,513	0,516	0,481	0,527	0,507	0,490	0,485	0,527	0,490	0,517	0,551	0,499
16	0,517	0,536	0,457	0,545	0,514	0,529	0,517	0,486	0,466	0,483	0,548	0,488
17	0,530	0,544	0,450	0,552	0,466	0,510	0,488	0,517	0,434	0,490	0,504	0,463
18	0,542	0,507	0,428	0,545	0,466	0,494	0,534	0,495	0,491	0,468	0,530	0,463
19	0,514	0,507	0,440	0,524	0,541	0,487	0,497	0,476	0,431	0,468	0,529	0,427
20	0,508	0,461	0,454	0,536	0,492	0,471	0,476	0,490	0,420	0,483	0,489	0,465
21	0,520	0,475	0,465	0,509	0,503	0,455	0,503	0,486	0,432	0,469	0,492	0,453
22	0,488	0,500	0,476	0,501	0,498	0,470	0,534	0,514	0,450	0,474	0,497	0,463
23	0,489	0,449	0,445	0,485	0,476	0,478	0,503	0,498	0,455	0,449	0,489	0,460
24	0,504	0,509	0,457	0,487	0,478	0,460	0,471	0,490	0,457	0,450	0,451	0,463
25	0,487	0,464	0,473	0,482	0,451	0,444	0,477	0,505	0,438	0,423	0,458	0,421
26	0,462	0,418	0,487	0,506	0,461	0,475	0,488	0,504	0,423	0,453	0,448	0,454
27	0,478	0,423	0,472	0,495	0,442	0,483	0,476	0,492	0,409	0,411	0,465	0,433
28	0,480	0,437	0,434	0,507	0,460	0,486	0,506	0,479	0,410	0,406	0,438	0,432
29	0,452	0,470	0,447	0,505	0,420	0,473	0,489	0,491	0,425	0,400	0,434	0,430
30	0,445	0,434	0,448	0,466	0,452	0,471	0,501	0,465	0,414	0,437	0,418	0,411

Figure 3- 6: Comparison of model Coherence scores for the 252 LDA models, highlighting the top12 models in white

3.5.5 Selecting the potential model using pyLDAvis

To assess the models, we inspect the 12 pyLDAVis discussed in (Sievert & Shirley, 2014) by looking at multiple elements precisely: a) a good breakdown of topics without any single topic dominating the space (i.e., the area of the topic bubble), b) a distributed spread of topics throughout the 2D space (topics separated and filling the entire space) and c) whether the top 10 tokens associated with each topic are semantically similar. Models where a topic dominates the space, or topics are concentrated in one quadrant, or the overlaps do not make sense semantically, the model is dropped from the process.

At this stage, ten models are dropped, narrowing down to 2 models for deeper inspection. Of note, as shown by the white cells in the heatmap in Figure 3-6, the top 2 models do not have the highest Coherence, but they are still strong contenders based on the pyLDAVis review. Figures 3-7 and 3-8 represent the pyLDAvis for the 15-topic and 17-topic models, respectively.

The parameters, Perplexity, and Coherence scores of the two viable model candidates that we narrow to for further assessment by MBC SMEs.

Parameter	Model 1	Model 2
Number of Topics	17	15
Frequent Words Cut-off	> 15%	> 30%
Infrequent Words Cut-off	20 Documents	15 Documents

Number of words after filtering	2,100	2,740
Perplexity	-7.0764	-7.0386
Coherence	0.552	0.551

Table 3- 6: Parameters for the two candidate models

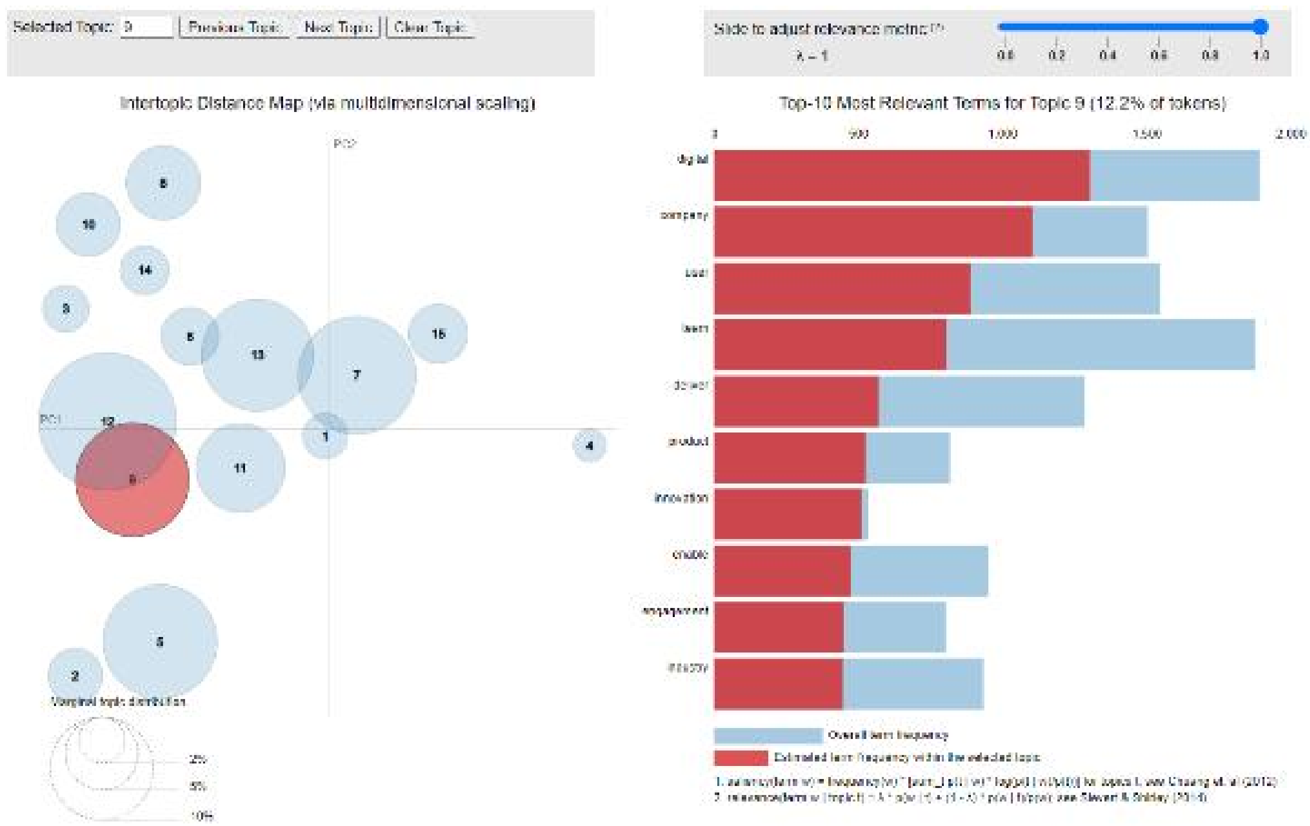


Figure 3- 7: pyLDAVis for the 15-topic model

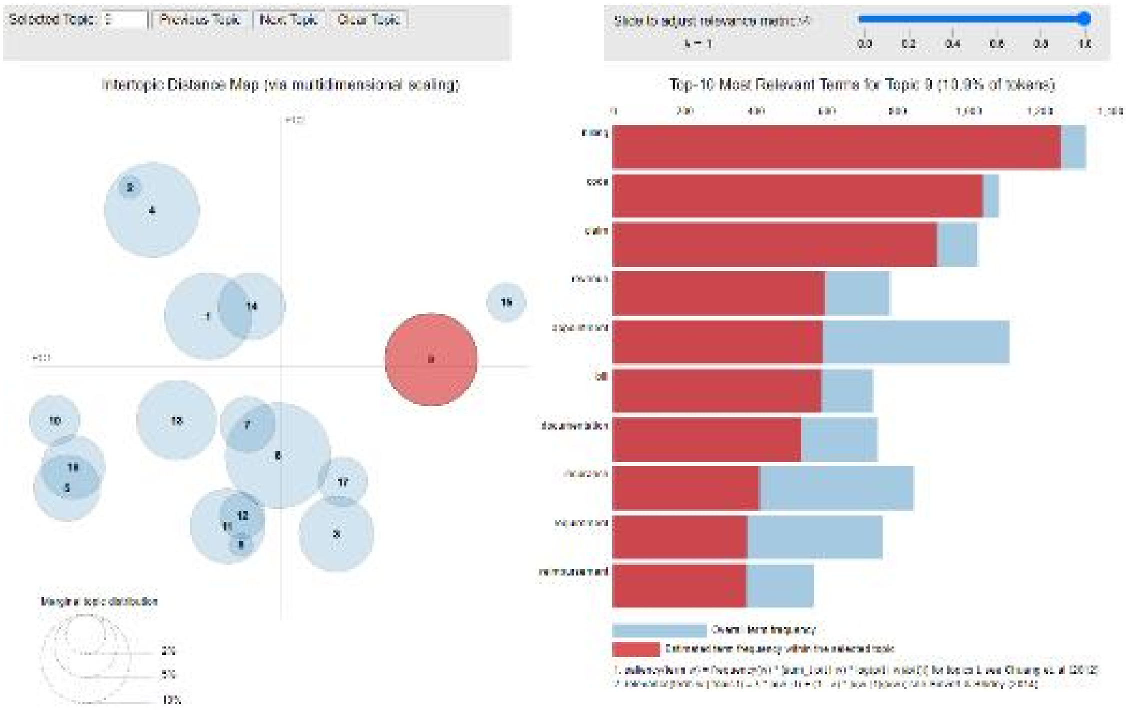


Figure 3- 8: pyLDAVis for the 17-topic model

3.6 Topic naming

In an exploratory topic modeling analysis, best practices highlight the need for domain expertise in evaluating model output . We do so in this research with the assistance of SMEs who identify the underlying theme for each topic and then assign topic names based on domain knowledge. Topic models do not explicitly label topics; instead, they probabilistically weight lists of words belonging to each topic. They use the most relevant words per topic and the most representative documents to assign names to the topics.

3.6.1 Review by SME In MBC operations

In this phase, the SME reviews the top ten most relevant words for each topic and the top two associated documents. The exercise introduces us to the first insights and gives a generic view of the potential topic names. We evaluate the consistency of the keywords and compare them to the most representative documents.

First, we assess each document’s top 30 relevant words by varying λ between 1.0 and 0.0. Word relevance, as defined in (Sievert & Shirley, 2014), is a weighted score of the term's probability and its lift. In line with the findings of (Sievert & Shirley, 2014), we use a weighting value of $\lambda = 0.6$ to determine the top ten human interpretable words. Where the words do not seem to make sense, we adjust λ to 0.0 and 1.0 to determine the 10 unique and 10 most frequent terms for a selected topic, respectively.

Next, we calculate the percentage each topic contributes to the documents in the corpus. Given that no single topic makes up 100% of any document, we extract each topic's top two most representative documents in the corpus. Table 3-7 and Table 3-8 reveal the top two documents for each topic. In our case, these weights are in the 0.87-0.99 range, meaning the preponderance of topic distribution within the document is for the topic of interest.

Topic No.	Topic Contribution	Title
1	0.9982	What is a Patient Health Questionnaire?
1	0.9976	What Do Patient Health Questionnaires Like PHQ9 Measure?
2	0.9973	Creating a COVID-19 Policy for Your Mental Health Practice
2	0.9962	How to Add a Virtual Care Link to Your GMB Listing
3	0.9962	Michigan's Bay-Arenac ISD Experience in Launching bhworks Software Platform
3	0.995	Copper Country School District conducts 'Super Smooth' SEL universal screening event using bhworks
4	0.9979	Comparing effectiveness of two medications by evaluating negative symptoms in patients diagnosed with schizophrenia
4	0.9974	Analyzing hospitalization rate, treatment switch, and effectiveness between two MDD drugs
5	0.9971	Mental Health Billing: 3 Ways to Increase the Odds That You'll Get Paid
5	0.996	In-House Billing and Revenue Cycle Management
6	0.9968	How Medication-Assisted Treatment Can Help Manage Opioid Addiction
6	0.9954	Submit Your Comments for the Updated CDC Guideline for Prescribing Opioids for Chronic Pain
7	0.9994	Using client feedback in psychotherapy training: An analysis of its influence on supervison and counselor self-efficacy.
7	0.9992	Alliance in couple therapy: Partner influence, early change and alliance patterns in a naturalistic sample.
8	0.9973	LGBTQIA+ Individuals Experience Disproportionate Health Risks
8	0.9971	The State of Mental Health in America 2020: Youth Prevalence and Access to Care
9	0.9974	SilverCloud raises $8.1M to accelerate delivery of solutions
9	0.997	Ksana Health Secures $2M Seed Round and Residency in Anthem Digital Incubator!
10	0.9944	Addressing the Tragedy of Veteran Suicide
10	0.9863	The Heart of a Warrior
11	0.8908	About us – Better Outcomes Now
11	0.8771	Who we serve (providers) – Greenspace Health
12	0.9984	What is work-life balance for your employees and how can employers spot the signs of employees having problems
12	0.9984	Self-Care and Coping with Life After Lockdown
13	0.9977	Integrated Behavioural Health
13	0.9977	The Importance of Positive Mental Health in Diabetes Management
14	0.9963	Unique programmes that can support children and young people's mental health - and their families
14	0.9957	Designing effective online mental health programmes for children and young people
15	0.9992	The outcome rating scale: A preliminary study of the reliability, validity and feasibility of a brief visual analog measure.
15	0.9982	The reliability and validity of the outcome rating scale: A replication study of a brief clinical measure.

Table 3- 7: Weight of the top two documents per topic for the 15-topic model

Topic No	Topic Contribution	Title
1	0.9988	Using technology to enhance clinical supervision.
1	0.9918	Using Feedback-Informed Treatment Software in Your Practice
2	0.997	What is a Patient Health Questionnaire?
2	0.9959	What Do Patient Health Questionnaires Like PHQ9 Measure?
3	0.9971	Team
3	0.9964	NextStep Solutions Leadership
4	0.9988	Alliance in couple therapy: Partner influence, early change and alliance patterns in a naturalistic sample.
4	0.9988	The Norway couple project: Lessons learned.
5	0.9965	Maintaining Body Positivity Throughout the Holiday Season and Beyond
5	0.9894	See the Change, Be the Change: Building Awareness to Prevent Eating Disorders
6	0.9815	Our Top Mental Health Motivation Tips
6	0.9781	Firefighter Zen: Thriving in Tough Times
7	0.9943	How The SUPPORT for Patients and Communities Act Helps Fix a 15-Year-Old Issue with Buprenorphine
7	0.9939	Easier to Prescribe Opioids Than Buprenorphine Experts Lament Patient Barriers to Medication-Assisted Treatment
8	0.9967	Best Psychology Magazines and Journals for Psychologists
8	0.9878	Clinical Advisory and Governance Board
9	0.9964	Flexible Workflows
9	0.9961	Three EHR Tools Behavioral Healthcare Facilities Need to Manage Growth and Increase Efficiency
10	0.9948	The Importance of Positive Mental Health in Diabetes Management
10	0.9943	Addressing the Psychological Impact of Diabetes
11	0.993	Hempfield Students Return to School with Universal Screening for Mental Health
11	0.9922	Michigan Chooses bhworks Software Platform for Statewide School Use to Address Youth Behavioral Mental Health
12	0.9979	Work-life balance: five pieces of the workplace wellbeing jigsaw
12	0.9975	What is work-life balance for your employees and how can employers spot the signs of employees having problems
13	0.9983	How do you solve a problem like engagement?
13	0.9964	Usage and Outcomes - What's the Right "Dose" for Patient Engagement?
14	0.9932	Our Solution
14	0.9914	What's the Impact of Collaborative Care? NeuroFlow Dives into Patient Outcomes
15	0.9963	PPP Loan Forgiveness: Essential Guide for Behavioral Health Practices
15	0.9945	How to Evaluate Credit Card Processing Options for Your Mental Health Practice
16	0.9964	The Trevor Project National Survey on LGBTQ Youth Mental Health 2021
16	0.9963	Addressing Cultural and Racial Disparities in Behavioral Healthcare
17	0.9959	How to Create a Great Behavioral Telehealth Patient Experience
17	0.9917	The Top Mental Health Software and Telehealth Therapy

Table 3- 8: Weight of the top two documents per topic for the 17-topic model

Finally, we compare the topic's key terms and the most representative documents. We examine for consistency. At the end of the process, we can roughly name a few topics from the model. Table 3-9 and 3-10 shows a list of documents compared to each topic's the keywords.

Topic No.	Top 10 Human Interpretable Words	Dominant Document 1	Dominant Document 2
1	Assessment, interview, phq, reminder, diagnosis, screener, questionnaire, DSM, disorder, appointment	What is a patient health questionnaire?	What do patient health questionnaires like PHQ9 measure?
2	Telehealth, virtual, security, video, visit, portal, HIPAA, secure, session, remotely	Creating a COVID-19 policy for your mental health practice	How to add a virtual care link to your GMB listing
3	Student, school, district, teen, family, screen, college, teacher, child, classroom	Michigan's Bay-Arenac ISD experience in launching Bhworks software platform	Copper Country School District conducts 'Super Smooth' SEL universal screen event using Bhworks.
4	Code, cohort, real, schizophrenia, analysis, category, drug, depressive, label, contain	Comparing the effectiveness of two medications by evaluating negative symptoms in patients diagnosed with schizophrenia	Analyzing hospitalization rate, treatment switch, and effectiveness between two MDD drugs
5	ehr, billing, software, claim, staff, revenue, bill, code, insurance, record	Mental Health Billing: 3 ways to increase the odds that you'll get paid	In-house billing and Revenue Cycle Management
6	Addiction, opioid, substance, recovery, drug, medication, pain, overdose, alcohol, prescription	How Medication-Assisted Treatment can help manage Opioid Addiction	Submit your comments to the updated CDC guideline for prescribing Opioids for chronic pain
7	Therapist, feedback, session, alliance, couple, dating, relationship, study, score, scale	Using client feedback in psychotherapy training: An analysis of its influence on supervision and counselor self-efficacy	Alliance in couple therapy: Partner influence, early change and alliance patterns in a naturalistic sample
8	Woman, black, community, adult, youth, illness, man, likely, eat, food	LGBTQIA+ individuals experience disproportionate health risks	The state of mental health in America 2020: youth prevalence and access to care
9	Digital, company, user, innovation, team, product, market, deliver, engagement, enable	Silvercloud raises $8.1M to accelerate delivery of solutions	Ksana Health secures $2M seed round and residency in Anthem Digital Incubator
10	Suicide, veteran, awareness, prevention, crisis, military, risk, suicidal, worker, PTSD	Addressing the tragedy of veteran suicide	The heart of a warrior
11	Measurement, progress, assessment, clinician, improvement, value, quality, information, theory, objective	About us	Who we serve (providers)
12	Feel, think, thing, stress, day, employee, really, come, start, lot	What is work-life balance for your employees, and how can employers spot the signs of employees having problems?	Self-care and coping with life after lockdown
13	Depression, disorder, anxiety, symptom, intervention, condition, chronic, primary, physical, online	Integrated behavioral health	The importance of positive mental health in diabetes management
14	Child, young, parent, autism, paediatric, caregiver, adolescent, family, rank, kid	Unique programs that can support children and young people's mental health - and their families	Designing effective online mental health programs for children and young people
15	Scale, rating, score, sample, validity, item, reliability, instrument, concurrent, administration	The outcome rating scale: A preliminary study of the reliability, validity, and feasibility of a brief visual analog measure	The reliability and validity of the outcome rating scale: A replication study of a brief clinical measure

Table 3- 9: Top two weighted documents for 15-topic model

Topic No.	Top 10 most relevant Words	Dominant document 1	Dominant document 2
1	Rating, supervision, supervisor, psychotherapy, counselor, alliance, effectiveness, inform, fit, score	Using technology to enhance clinical supervision	Using Feedback-Informed Treatment Software in Your Practice
2	Phq, questionnaire, phase, item, score, smart, disease, screener, stage, psychotherapy	What is a Patient Health Questionnaire?	What Do Patient Health Questionnaires Like PHQ9 Measure?
3	Innovation, market, product, officer, chief, leader, innovative, analytic, announce, award	Team	NextStep Solutions Leadership
4	Score, couple, rating, alliance, sample, analysis, validity, reliable, item, correlation	Alliance in couple therapy: Partner influence, early change and alliance patterns in a naturalistic sample	The Norway couple project: Lessons learned
5	Sleep, eat, body, holiday, alcohol, food, awareness, healthy, habit, medium	Maintaining Body Positivity Throughout the Holiday Season and Beyond	See the Change, Be the Change: Building Awareness to Prevent Eating Disorders
6	Vendor, lot, implementation, really, try, talk, sure, customer, worry, transition	Our Top Mental Health Motivation Tips	Firefighter Zen: Thriving in Tough Times
7	Addiction, opioid, medication, drug, recovery, overdose, prescribe, prescription, buprenorphine, mat	How The SUPPORT for Patients and Communities Act Helps Fix a 15-Year-Old Issue with Buprenorphine	Easier to Prescribe Opioids Than Buprenorphine Experts Lament Patient Barriers to Medication-Assisted Treatment
8	Psychology, myth, publish, publication, journal, peer, psychological, director, reality, rehabilitation	Best Psychology Magazines and Journals for Psychologists	Clinical Advisory and Governance Board
9	Billing, code, claim, bill, revenue, documentation, appointment, reimbursement, payer, insurance	Flexible Workflows	Three EHR Tools Behavioral Healthcare Facilities Need to Manage Growth and Increase Efficiency
10	Chronic, pain, diabete, disease, cancer, diabetes, psychological, schizophrenia, cbt, heart	The Importance of Positive Mental Health in Diabetes Management	Addressing the Psychological Impact of Diabetes
11	Student, school, worker, black, crisis, education, national, funding, district, counseling	Hempfield Students Return to School with Universal Screening for Mental Health	Michigan Chooses bhworks Software Platform for Statewide School Use to Address Youth Behavioral Mental Health
12	Employee, workplace, employer, wellbeing, culture, hire, manager, teen, job, candidate	Work-life balance: five pieces of the workplace wellbeing jigsaw	What is work-life balance for your employees and how can employers spot the signs of employees having problems
13	App, supporter, content, young, module, internet, cognitive, icbt, usage, activity	How do you solve a problem like engagement?	Usage and Outcomes - What's the Right "Dose" for Patient Engagement?
14	Primary, checklist, interview, physician, screening, severity, psychiatric, diagnose, integration, pediatric	Our Solution	What's the Impact of Collaborative Care? NeuroFlow Dives into Patient Outcomes
15	Fee, pay, payment, credit, insurance, card, agreement, portal, amount, expense	PPP Loan Forgiveness: Essential Guide for Behavioral Health Practices	How to Evaluate Credit Card Processing Options for Your Mental Health Practice
16	Suicide, veteran, woman, suicidal, youth, percent, prevention, man, attempt, military	The Trevor Project National Survey on LGBTQ Youth Mental Health 2021	Addressing Cultural and Racial Disparities in Behavioral Healthcare

17	Telehealth, virtual, video, security, visit, appointment, hipaa, remote, rural, remotely	How to Create a Great Behavioral Telehealth Patient Experience	The Top Mental Health Software and Telehealth Therapy

Table 3- 10: Review of relevant words against the top two documents for the 17-topic model

3.6.2 Topic naming by SMEs

We introduce the two candidate topic models to two clinically trained SMEs who are provided with a breakdown of each model, including the first ten most relevant words. The SMEs agree on the names of most topics with ease. In instances where it is not easy to label a topic, we adjust the value λ to 1.0 and 0.0 for the ten most frequent and the ten most unique words in that topic to give SMEs more insight into the topic. Without comparing with dominant documents of each topic, the SME name the topic as shown in Table 3-8 and table 3-9 for the 15-topic model and 17-topic model, respectively.

Topic No.	Top 10 most relevant Words	Topic Name
1	Assessment, interview, phq, reminder, diagnosis, screener, questionnaire, dsm, disorder, appointment	MBC intake
2	Telehealth, virtual, security, video, visit, portal, hipaa, secure, session, remotely	Telehealth
3	Student, school, district, teen, family, screen, college, teacher, child, classroom	School-Based Treatment
4	Code, cohort, real, schizophrenia, analysis, category, drug, depressive, label, contain	Drug Study
5	ehr, billing, software, claim, staff, revenue, bill, code, insurance, record	Reimbursement
6	Addiction, opioid, substance, recovery, drug, medication, pain, overdose, alcohol, prescription	Substance Abuse
7	Therapist, feedback, session, alliance, couple, rating, relationship, study, score, scale	Therapeutic Alliance
8	Woman, black, community, adult, youth, illness, man, likely, eat, food	Community Mental Health
9	Digital, company, user, innovation, team, product, market, deliver, engagement, enable	MBC Platform
10	Suicide, veteran, awareness, prevention, crisis, military, risk, suicidal, worker, ptsd	Veterans
11	Measurement, progress, assessment, clinician, improvement, value, quality, information, theory, objective	Value-Based Care
12	Feel, think, thing, stress, day, employee, really, come, start, lot	Therapy Process
13	Depression, disorder, anxiety, symptom, intervention, condition, chronic, primary, physical, online	Integrated Healthcare
14	Child, young, parent, autism, pediatric, caregiver, adolescent, family, rank, kid	Family and Autism
15	Scale, rating, score, sample, validity, item, reliability, instrument, concurrent, administration	Psychometrics

Table 3- 11: Topic names for the 15-topic model after the review by SMEs

Topic No.	Top 10 most relevant Words	Topic Name
1	Rating, supervision, supervisor, psychotherapy, counselor, alliance, effectiveness, in form, fit, score	Clinical supervision
2	Phq, questionnaire, phase, item, score, smart, disease, screener, stage, psychotherapy	We could not name this
3	Innovation, market, product, officer, chief, leader, innovative, analytic, announce, award	Start-ups
4	Score, couple, rating, alliance, sample, analysis, validity, reliable, item, correlation	Psychometrics
5	Sleep, eat, body, holiday, alcohol, food, awareness, healthy, habit, medium	Grief/loss
6	Vendor, lot, implementation, really, try, talk, sure, customer, worry, transition	We could not name this
7	Addiction, opioid, medication, drug, recovery, overdose, prescribe, prescription, buprenorphine, mat	Substance Abuse
8	Psychology, myth, publish, publication, journal, peer, psychological, director, reality, rehabilitation	Substance Use Treatment
9	Billing, code, claim, bill, revenue, documentation, appointment, reimbursement, payer, insurance	Financial
10	Chronic, pain, diabete, disease, cancer, diabetes, psychological, schizophrenia, CBT, heart	CBT for Chronic Health Conditions
11	Student, school, worker, black, crisis, education, national, funding, district, counseling	Youth Schools
12	Employee, workplace, employer, wellbeing, culture, hire, manager, teen, job, candidate	Workplace
13	App, supporter, content, young, module, internet, cognitive, iCBT, usage, activity	Internet-Based Treatment
14	Primary, checklist, interview, physician, screening, severity, psychiatric, diagnose, integration, pediatric	Integrated Healthcare
15	Fee, pay, payment, credit, insurance, card, agreement, portal, amount, expense	EHR
16	Suicide, veteran, woman, suicidal, youth, percent, prevention, man, attempt, military	Veterans
17	Telehealth, virtual, video, security, visit, appointment, hipaa, remote, rural, remotely	Telemental Health

Table 3- 12: Topic names for the 17-topic model after the review by SMEs

3.6.3 Naming validation

At this stage, SMEs provide a list of names for each of the dominant topics identified. The SME judgment is based on their knowledge of the subject area as they relate the topic keywords with the content of the dominant document for each topic. To validate the name, we undertake a naming justification process to confirm the topic naming. This section describes the justification process.

Topic 1: MBC intake: is a practice involving the diagnostic assessment of the quality of mental health with the help of instruments such as interviews and questionnaires. PHQ-9 and DSM are tools used to assess mental health (Breedvelt et al., 2020; Connors et al., 2021; Mitchell et al., 2016; Stein et al., 2013; Verhagen et al., 2022). The pyLDAvis reveals the top ten relevant words for the MBC intake topic: assessment, interview, phq, reminder, diagnosis, screener, questionnaire, dsm, disorder, and appointment. The terms align with the topic.

Topic 2: Telehealth: Through information and communication technologies, telehealth brings professional healthcare closer to mental health patients constrained by geographical locations, schedules, or quarantine (Monaghesh & Hajizadeh, 2020). Mental healthcare service providers can also remotely reach out to as many patients as possible. To access mobile treatment, a patient has to create a user account which requires input information, e.g., name, email address, date of birth, address, phone contact, and banking details. Providers must meet specific standards to protect patients' privacy data (Tuckson et al., 2017). The top ten relevant words; telehealth, virtual, security, video, visit, portal, hipaa, secure, session, and remotely justify the second topic as telehealth.

Topic 3 -School-Based Treatment: Involves mental health treatment in school-going children. Mental health treatment programs have been designed for school-going to improve outcomes for youths by boosting self-confidence and social skills (Manion et al., 2013; Salerno, 2016). Parents and teachers are critical in treating youth mental health(Christian et al., 2018; Evans et al., 2004). The top 10 relevant words; student, school, district, teen, family, screen, college, teacher, child, and classroom, are important in discussing the school-based treatment themes.

Topic 4 -Drug Study: Involves clinical investigation of a drug to determine its characteristics, efficiency, and safety for human administration (Holbein, 2009). The relevant words; Code, cohort, real, schizophrenia, analysis, category, drug, depressive, label, and contain, are found to be representative of the topic by the SMEs.

Topic 5 -Reimbursement: Reimbursement is about how much payers are willing to pay for covered services and products on behalf of their plan subscribers (Garrison & Towse, 2017). EHR, billing, software, claim, staff, revenue, bill, code, insurance, and record are the relevant terms in labeling this topic as reimbursement. EHRs are software generally recognized for managing patient records and administrative healthcare tasks like billing and claim. Physicians submit billing data that can be used for reimbursement by payors (Spady et al., 2004).

Topic 6 -Substance Abuse: substance abuse is characterized by the misuse of drugs that result in mental health issues. Opioid is one of the drugs a patient can overdose on to reduce severe pain. Alcohol addiction is another form of substance abuse. Words, e.g., addiction, opioid, substance, recovery, drug, medication, pain, overdose, alcohol, and prescription, represent the topic well.

Topic 7 -Therapeutic Alliance: Therapeutic alliance entails a good working relationship between a patient and a healthcare professional where patients are free to express themselves. Therapists collect feedback from clients, which they use to rate the sessions by applying several rating scales to assess therapeutic alliance. Therapist, feedback, session, alliance, couple, rating, relationship, study, score, and scale, describe the theme well.

Topic 8 -Community Mental Health: Encompasses a group of underserved people categorized by age, gender, race, disabilities, religion, politics, sexuality, etc. Although some relevant words do not specifically define community health, e.g., likely, eat, and food, most suggest community mental health, i.e., Woman, black, community, adult, youth, illness, and man.

Topic 9 - MBC Platform: New companies are merging in the space of MBC in BHC, which is why the top relevant words; digital, company, user, innovation, team, product, market, deliver, engagement, and enable best summarize the topic.

Topic 10 - Veterans: Veterans are likely to be diagnosed with mental health issues. There tends to be a rise in diagnoses of posttraumatic stress disorder among veterans after war (Seal et al., 2009). The top relevant words; Suicide, veteran, awareness, prevention, crisis, military, risk, suicidal, worker, and PTSD, associated with veteran mental health.

Topic 11 - Value-Based Care: involves the delivery of quality healthcare to patients and reimbursement based on patient outcomes (Garrison & Towse, 2017). Mental health providers need to be able to measure treatment quality continuously through evidence-based care practices (Conrad, 2015). The keywords; Measurement, progress, assessment, clinician, improvement, value, quality, information, theory, and objective, are in line with VBC.

Topic 12 - Therapy Process: Labeling this topic was challenging, given the top relevant words; feel, think, thing, stress, day, employee, really, come, start, and lot. The terms relate to emotional processing, which points us to the therapy process.

Topic 13 - Integrated Healthcare: involves the collaboration between healthcare practitioners with varying expertise to manage their patient’s physical, behavioral, and mental health concerns. Depression, disorder, anxiety, symptom, intervention, condition, chronic, primary, physical, and online, are the top relevant words our model reveals. In cases where a chronic illness compromises the mental stability of a patient, therapists would require understanding the root cause of the instability. Working with the primary healthcare provider can lead to better outcomes.

Topic 14 - Family and Autism: Autism is characterized by communication and social skills challenges, especially in children. Families of such children are usually anxious and require emotional stability to care for their little ones. The top relevant word; Child, young, parent, autism, pediatric, caregiver, adolescent, family, rank, and kid, are the basis for the topic name.

Topic 15 - Psychometrics: is the assessment of perceptions, emotions, attitudes, and personality traits directly through a set of observed variables (Vitoratou & Pickles, 2017). The model summarizes relevant words for psychometrics as; scale, rating, score, sample, validity, item, reliability, instrument, concurrent, and administration. Validity and reliability are examples of measures applied in scales' assessment to minimize psychometrics errors.

During the naming phase of the 17-topic model, we discover that some topics have the same labels as the 15-topic models, e.g., psychometrics, substance abuse, integrated healthcare, and veterans. Although other topics have slightly different names, they talk about the same things, e.g., start-ups and MBC platforms, finance and reimbursement, youth schools and school-based treatment, and telemental health and telehealth. The SME needed more information to easily name topics two and six using the most relevant words.

Clinical supervision: relevant words; rating, supervision, supervisor, psychotherapy, counselor, alliance, effectiveness, inform, fit, and score are good candidates in labeling this topic. Clinical supervision is the support given to less qualified professionals by their superiors to ensure effective healthcare.

Grief and loss: Grief is a result of a loss. When people grieve, they tend to have shifts in behavior and emotion. For example, some people may tend to sleep or eat a lot when they grieve, while others may not want to eat at all. Sleep, eat, body, holiday, alcohol, food, awareness, healthy, habit, and medium are the relevant words to label this topic.

Substance Use Treatment: refers to the treatment of addiction. The relevant words; Psychology, myth, publish, publication, journal, peer, psychological, director, reality, and rehabilitation, are hints to substance use treatment. Rehabilitation, for instance, is the therapy process that aims to restore one's health and life to normal after an addiction. Myth, publish, publication and journal in this context point to research on substance use treatment.

CBT for Chronic Health Conditions: refers to psychotherapy for people with heart, diabetes, etc. The relevant words; chronic, pain, diabetes, disease, cancer, diabetes, psychological, schizophrenia, CBT, and heart are good components for the topic name.

Workplace: The theme talks about a healthy working environment for workers. Employee, workplace, employer, wellbeing, culture, hire, manager, teen, job, and candidate qualify the topic name.

Internet-Based Treatment: refers to treatment over the internet, through apps. Relevant words can be classified into the internet (app, supporter, content, module, and internet) and treatment (cognitive, ICBT, and activity).

EHR: Manages patient records and administrative healthcare tasks like billing and claim. EHR and reimbursement topics tend to talk about the same thing. This can be explained by the fact that EHRs enable reimbursement. Relevant words we consider in naming the topic are; Fee, pay, payment, credit, insurance, card, agreement, portal, amount, and expense.

At the end of the naming phase, topics in the 15-topic model were named, while the SMEs still faced difficulty in the topic interpretability of topics in the 17-topic model. Only 15 out of 17 topics were named. As a result, we drop the 17-topic model and consider the 15-topic model for further analysis.

Table 3- 13: Topics identified and named following SME review of the 17-topic model

3.6.4 Validation of topic names with dominant documents

We compare the topic labels to the two dominant documents in the previous stage, as shown in Table 3:9. We realize that the topic names make much sense with respect to the document titles. The documents for VBC could be more straightforward by just looking at the titles. To find clarity, we read the content of the documents. We find aspects of VBC and conclude that all topics represent our corpus well. Table 3-14 shows the content of the dominant document 1 for the VBC topic.

Topic Name	Dominant Document 1	Dominant Document 2
MBC intake	What is a patient health questionnaire?	What do patient health questionnaires like PHQ9 measure?
Telehealth	Creating a COVID-19 policy for your mental health practice	How to add a virtual care link to your GMB listing
School-Based Treatment	Michigan's Bay-Arenac ISD experience in launching Bhworks software platform	Copper Country School District conducts 'Super Smooth' SEL universal screen event using Bhworks.
Drug Study	Comparing the effectiveness of two medications by evaluating negative symptoms in patients diagnosed with schizophrenia	Analyzing hospitalization rate, treatment switch, and effectiveness between two MDD drugs
Reimbursement	Mental Health Billing: 3 ways to increase the odds that you'll get paid	In-house billing and Revenue Cycle Management
Substance Abuse	How Medication-Assisted Treatment can help manage Opioid Addiction	Submit your comments to the updated CDC guideline for prescribing Opioids for chronic pain
Therapeutic Alliance	Using client feedback in psychotherapy training: An analysis of its influence on supervision and counselor self-efficacy	Alliance in couple therapy: Partner influence, early change and alliance patterns in a naturalistic sample
Community Mental Health	LGBTQIA+ individuals experience disproportionate health risks	The state of mental health in America 2020: youth prevalence and access to care
MBC Platform	Silvercloud raises $8.1M to accelerate delivery of solutions	Ksana Health secures $2M seed round and residency in Anthem Digital Incubator
Veterans	Addressing the tragedy of veteran suicide	The heart of a warrior
Value-Based Care	About us – Better Outcomes Now	Who we serve (providers) – Greenspace Health
Therapy Process	What is work-life balance for your employees and how can employers spot the signs of employees having problems?	Self-care and coping with life after lockdown
Integrated Healthcare	Integrated behavioral health	The importance of positive mental health in diabetes management
Family and Autism	Unique programs that can support children and young people's mental health - and their families	Designing effective online mental health programs for children and young people
Psychometrics	The outcome rating scale: A preliminary study of the reliability, validity, and feasibility of a brief	The reliability and validity of the outcome rating scale: A replication study of a brief

	visual analog measure	clinical measure

Table 3- 14: A comparison of the topic labels with the two dominant documents

Topic	Value-based care
Document title	About us
Text	Better Outcomes Now (BON) is the true web application of Partners for Change Outcome Management System (PCOMS). BON is designed by Dr. Barry L. Duncan, the developer of the clinical process of PCOMS, the impetus for its scientific credibility, and the most successful at its implementation. Empirically proven to improve outcomes and efficiency, a SAMHSA evidence based practice Demonstrates effectiveness to funders Can be used across orientations and problems or diagnoses allowing you to be evidence based across all clients Cost effective implementation compared to other evidence based practices Operationalizes client privilege and individually tailored services Decreases length of stay, drop outs, and no shows Quality improvement strategy at both individual and agency levels Disseminated across the US, Canada, and worldwide; PCOMS measures translated in languages. No Protected Health Information required or collected; Highly secure website

Table 3- 15: Text of dominant document 1 for the value-based care topic

4 Results and Analysis

The SME provides the required review of the candidate models, labels the topics, and assesses each model's interpretability. In this section, we present the results of the modeling, which results in two models of 15 and 17 dominant topics, which, after the qualitative evaluation, we select only the model with 15 dominant topics. In this part, we model topics, topic correlation, topic dominance across document types and companies, and company correlation.

The modeling results in the identification of 15 dominant topics with a total of 1,719 documents in the proportion as shown in Figure 4-1

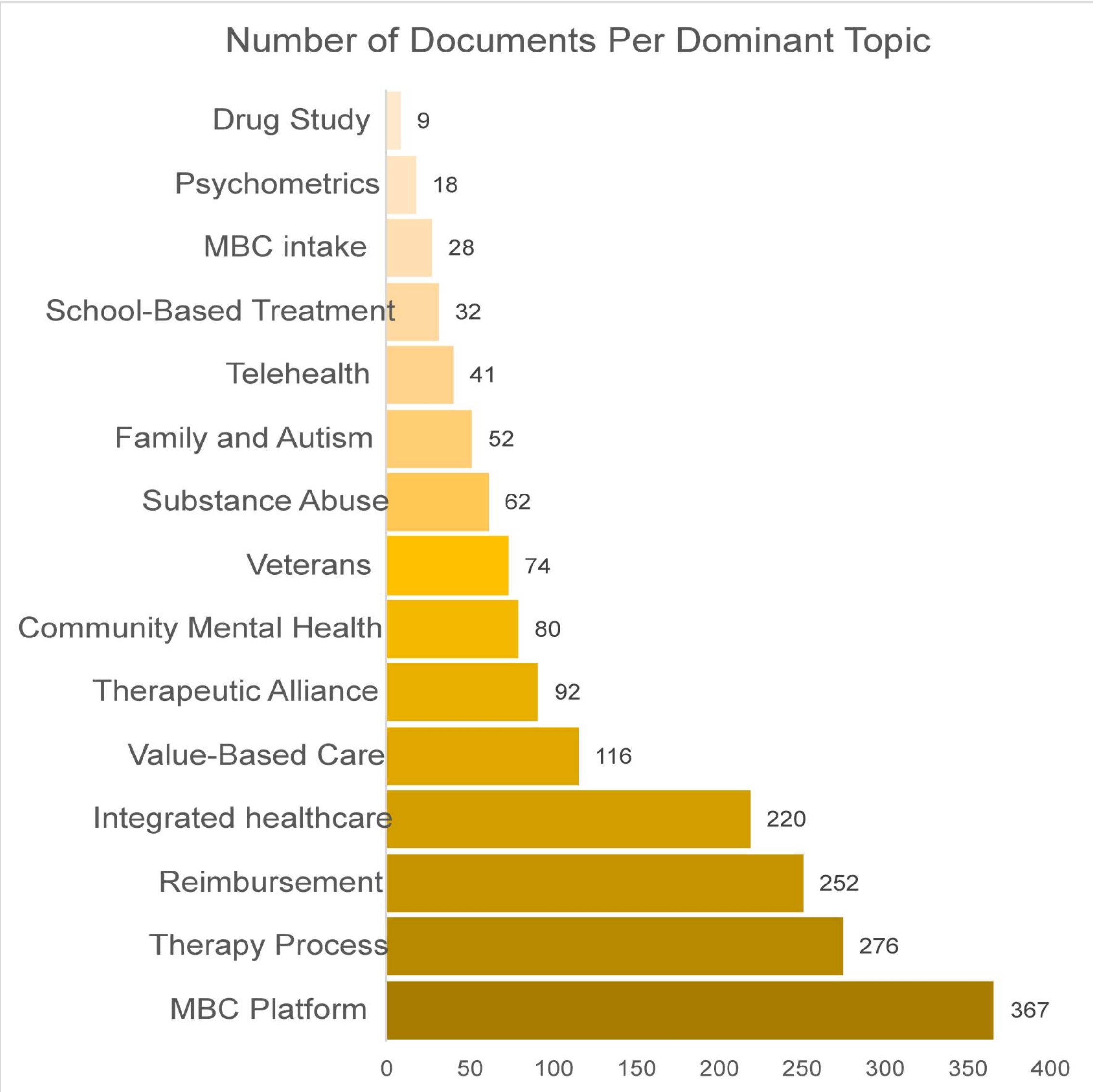


Figure 4- 1: Proportion of documents in each dominant topic

4.1 Dominant topics

This study has identified ten dominant topics with the associated key words as shown in Table 4-1.

Topic Name	Top 10 most relevant Words	Topic Name	Top 10 most relevant Words	Topic Name	Top 10 most relevant Words
MBC intake	Assessment, interview, phq, reminder, diagnosis, screener, questionnaire, dsm, disorder, appointment	**Telehealth**	Telehealth, virtual, security, video, visit, portal, hipaa, secure, session, remotely	**School-Based Treatment**	Student, school, district, teen, family, screen, college, teacher, child, classroom
Drug Study	Code, cohort, real, schizophrenia, analysis, category, drug, depressive, label, contain	**Reimbursement**	ehr, billing, software, claim, staff, revenue, bill, code, insurance, record	**Substance Abuse**	Addiction, opioid, substance, recovery, drug, medication, pain, overdose, alcohol, prescription
Therapeutic Alliance	Therapist, feedback, session, alliance, couple, rating, relationship, study, score, scale	**Community Mental Health**	Woman, black, community, adult, youth, illness, man, likely, eat, food	**MBC Platform**	Digital, company, user, innovation, team, product, market, deliver, engagement, enable
Veterans	Suicide, veteran, awareness, prevention, crisis, military, risk, suicidal, worker, ptsd	**Value-Based Care**	Measurement, progress, assessment, clinician, improvement, value, quality, information, theory, objective	**Therapy Process**	Feel, think, thing, stress, day, employee, really, come, start, lot
Integrated Healthcare	Depression, disorder, anxiety, symptom, intervention, condition, chronic, primary, physical, online	**Family and Autism**	Child, young, parent, autism, pediatric, caregiver, adolescent, family, rank, kid	**Psychometrics**	Scale, rating, score, sample, validity, item, reliability, instrument, concurrent, administration

Table 4- 1: The ten dominant topics

4.2 Topic weights distributions

The first analysis we perform is the distribution of topics. Figures 4-2, 4-3, and 4-4 show histograms of the topic weights distributed within the corpus for those documents, including the topic (i.e., topic weight > 0 in a document). Given that there are 15 topics, and most appear in only a subset of documents, we see that topics skew to the left towards zero weight. The skewness is because most documents have two to three significantly weighted topics.

The histograms at the top of Figure 4-2 have a denser distribution of topics. This distribution implies that MBC providers predominantly discuss the topic under the MBC platform, therapy process, reimbursement, integrated healthcare, and value-based care themes. On the contrary, MBC intake, family and autism, psychometrics, school-based treatment, and drug study rarely dominate a document, given how bars appear on the right-hand side of each histogram. The weak distribution means that MBC vendors irregularly post topics under these themes.

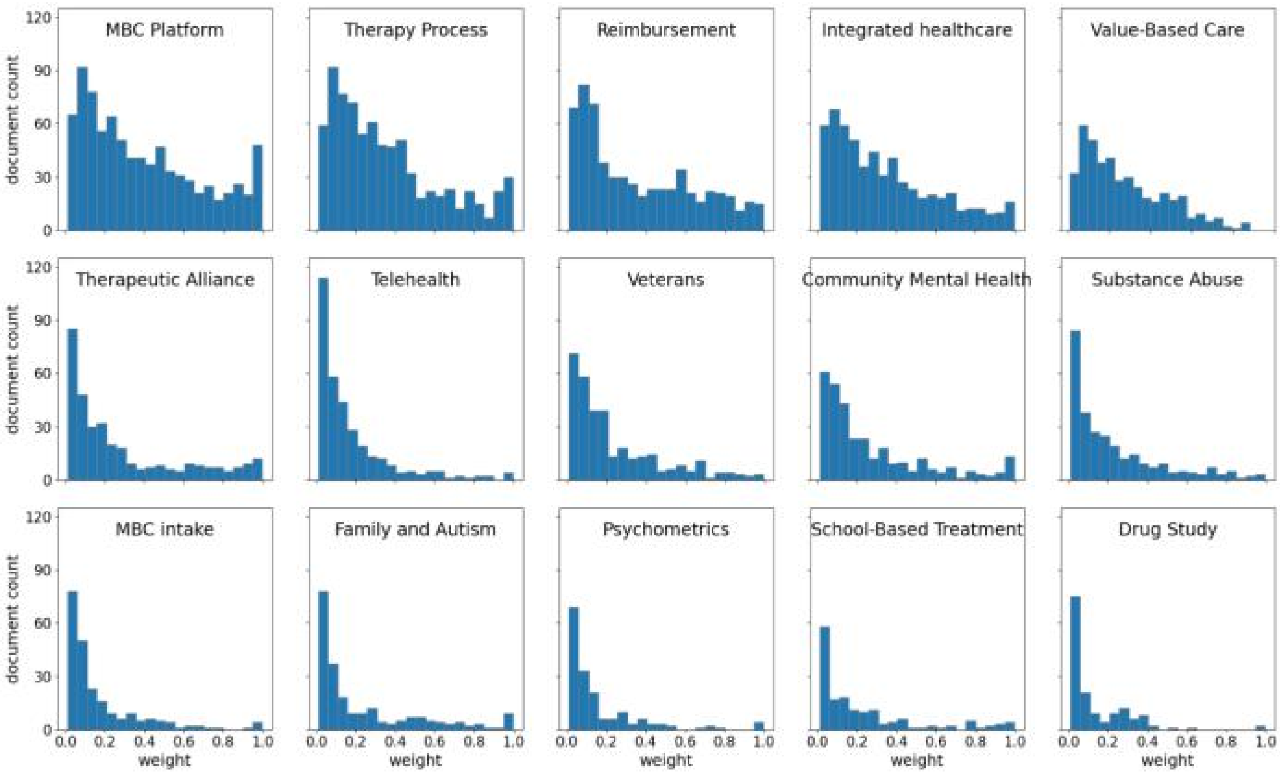


Figure 4- 2: Histograms showing document distributions in six of the 15 topics

4.3 Topic correlations

The following analysis investigates the correlations between topics within documents across the corpus. Given that some documents contain multiple topics, correlation of topics is checked for topics that appear together in the documents. Figure 4-5 shows a pairwise heatmap view of topic correlations. We use a bone color scale to highlight values further, with positively correlated topics being closer to white and negatively correlated topics being closer to black. We notice that the correlations between topics are weak, which is understandable considering that some topics weigh more than 80% in documents where they are presented.

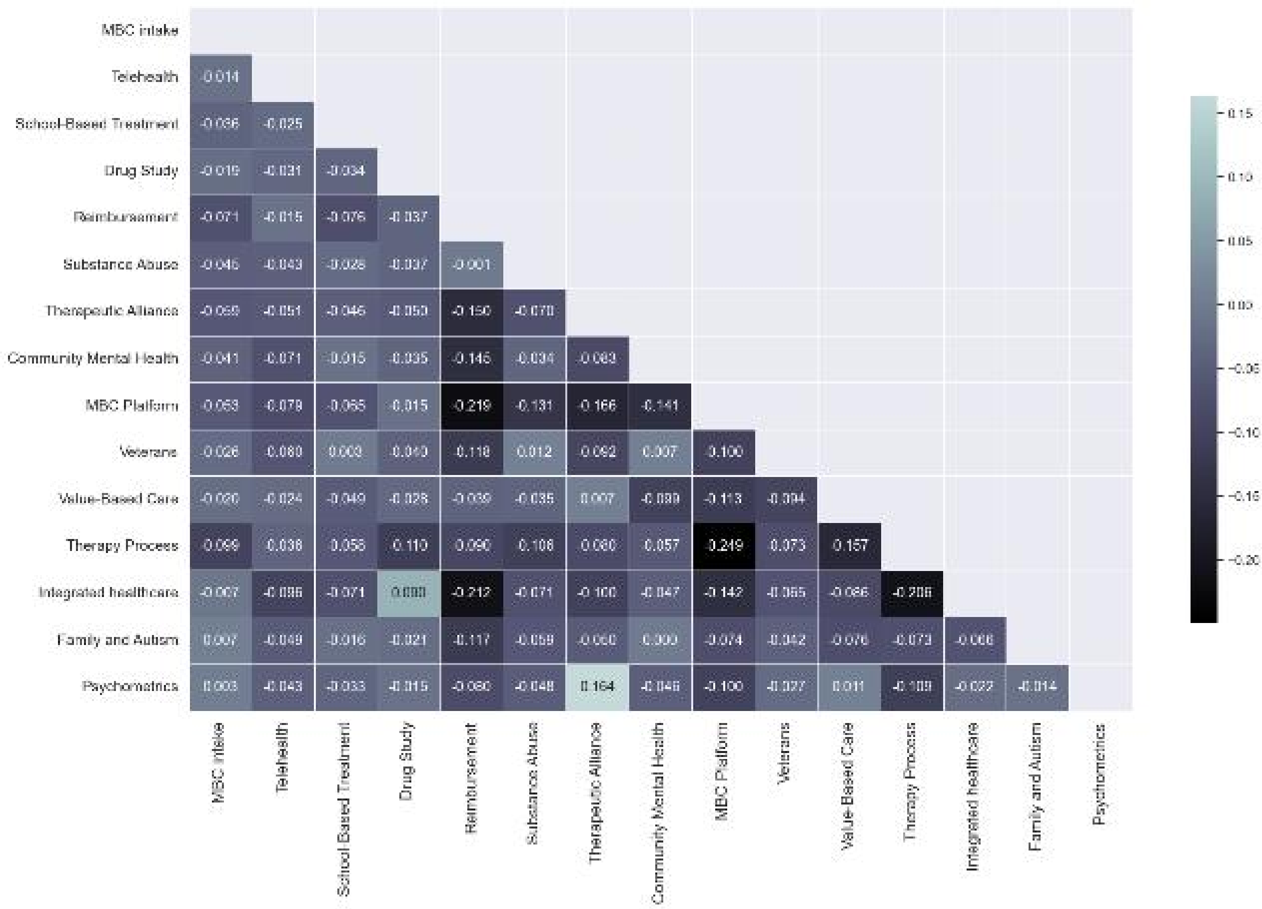


Figure 4- 5: Topic correlations

In addition to the topic correlations, we also investigate the topics whose correlation was either highly positive or negative, and we discover a pattern that is exhibited in Table 4-1 below. The most negatively correlated pair is the Therapy process and MBC platform, while on the other extreme, Psychometrics and Therapeutic alliance exhibit the highest positive correlation.

The top two positive correlations, as shown in Table 4-1, are psychometrics versus therapeutic alliance and integrated behavioral versus drug study healthcare. The rationale behind the positive correlation between topics is that they often appear in the same documents. For example, providers posting about therapeutic alliance include psychometric-related topics and vice-versa. The correlation between psychometrics and therapeutic alliance can also be identified by how they appear in research studies (Accurso et al., 2013; Bickman et al., 2012).

Conversely, for negative relationships, the more vendors write about a particular topic, the less they write about the other. The negative correlations point to the need for vendors to emphasize the impact of MBC on reimbursement and therapy processes in their content. In Table 4-1, MBC platforms versus therapy process and MBC platforms versus reimbursement are the most negatively correlated themes. We did not expect to get negative correlations between these categories. Since MBC companies tend towards VBC (Coley et al., 2020; Connors et al., 2021; Lewis et al., 2019b), we expect to see companies posting about how MBC platforms are positively influencing reimbursement. Similarly, with the therapy process, we presume increased efficiency with technological developments (J. C. Fortney et al., 2017; Lewis et al., 2019b; Scott & Lewis, 2015).

Top 5 negatively correlated topics	Therapy Process	MBC Platform	-0.249
	MBC Platform	Reimbursement	-0.219
	Integrated Healthcare	Reimbursement	-0.212
	Integrated Healthcare	Therapy Process	-0.206
	MBC Platform	Therapeutic Alliance	-0.166
Top 5 positively correlated topics	Veterans	Community Mental Health	0.007
	Psychometrics	Value-Based Care	0.011
	Veterans	Substance Abuse	0.012

	Integrated Healthcare	Drug Study	0.090
	Psychometrics	Therapeutic Alliance	0.164

Table 4- 2: Top five negatively and positively correlated topics

4.4 Company correlations

We then analyze the relationships between the companies within the corpus to ascertain those that discuss similar topics. Considering that all companies in the corpus provide MBC solutions, we expect to find strong positive correlations between them. Figure 4-4 presents a pairwise heatmap view of company correlations. We use a bone color scale on the right of Figure 4-6 to highlight values further, with positively correlated topics tending towards white and negatively correlated topics towards black, indicated in the scale range at the right.

The strongest positive relationships are between; Mirah versus Greenspace, Neuroflow versus Tridiuum, Holmusk versus Ksana health, Neuroflow versus SilverCloud, and Owl versus Ksana Health, with correlation values over 90%. This relationship is a good representation of the competitors. On the other hand, BHworks and CelestHealth have the weakest relationships with other companies. In the following analysis, we explore the dominant topics in each company.

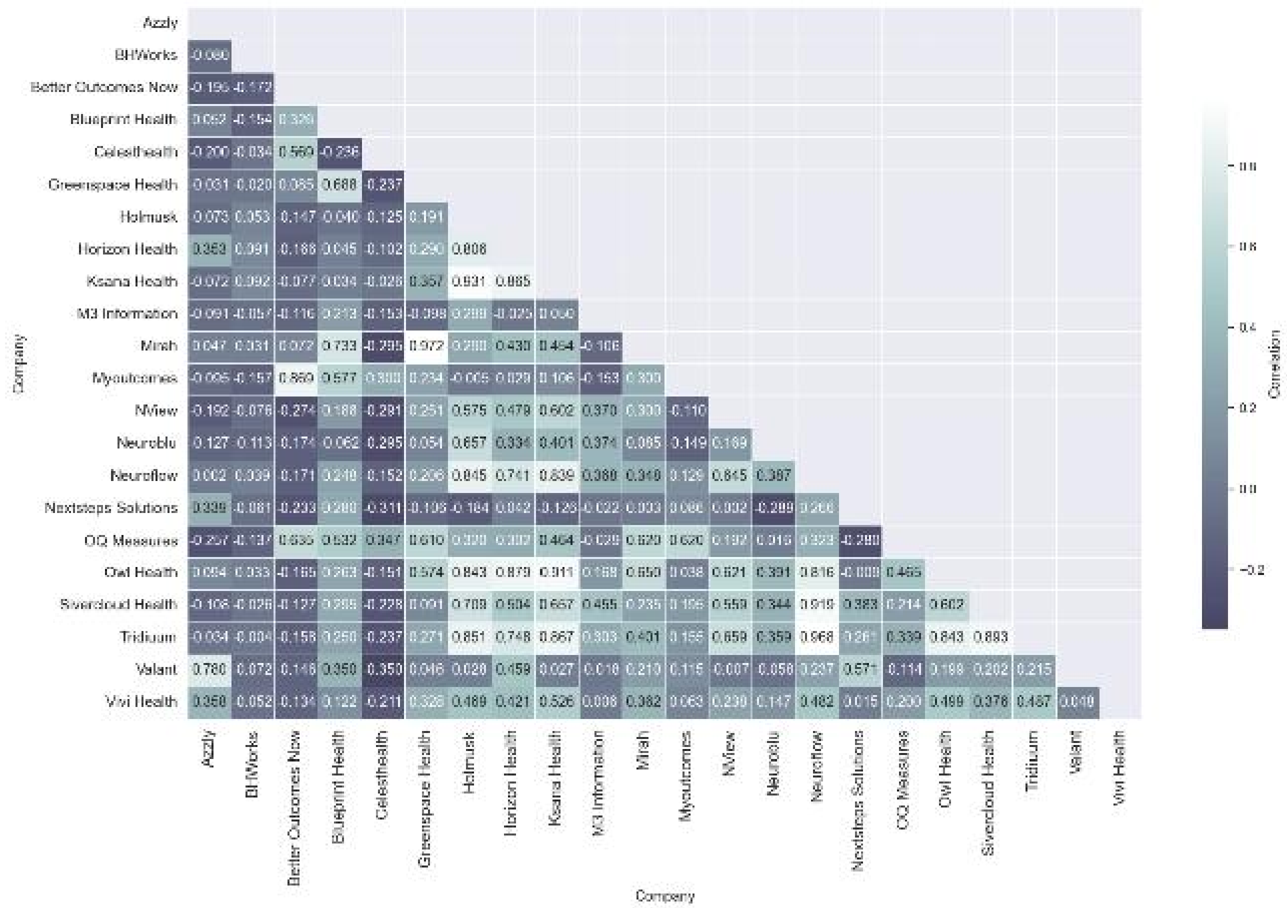


Figure 4- 7: Company Correlation

4.5 Topic prevalence by company

In this analysis, we inspect the dominant discussions in each company. Figure 4-8 presents a Green-Yellow-White color scale heatmap indicating the dominance of topics in each company, with green highlighting the highest values and white zero scores.

Generally, all other companies are in stiff competition with MBC companies in posting about the MBC Platform. This buzz around the topic proves that MBC in the BHC arena is significantly evolving. An exciting discovery is that Ksana Health publishes material whose content is 80% about the MBC platform, and M3 Information posts more content and integrated healthcare. Mirah and Greenspace Health are detected to focus on similar topics in a similar order of priority, i.e., they are centering most of their conversations around value-based care and talking less about the therapy process. Topics such as the MBC platform, value-based care, and therapy process are talked about by most companies. In contrast, drug studies and MBC intake are posted by less than a handful of the companies in our corpus.

This kind of analysis provides insights into competitors' contributions toward the evolution of MBC in BHC. With such insights, companies can improve their solutions and provide valuable resources to potential clients/customers.

Company	MBC intake	Telehealth	Drug Study	Reimbursement	Substance Abuse	Therapeutic Alliance	Community Mental He	MBC Platform	Veterans	Value-Based Care	Therapy Process	Psychometrics	School-Based Treatme	Family and Autism	Integrated healthcare
Azzly		0.2%		50.7%	25.7%		0.9%	3.4%	3.4%	8.0%	6.8%			0.1%	0.8%
BHWorks				6.2%				11.9%	6.4%	2.8%	6.5%		66.1%		
Celesthealth					6.2%	18.9%		6.3%	30.9%			19.0%	6.1%	12.7%	
Holmusk			5.0%		2.5%			63.1%						2.5%	26.9%
Mirah								25.0%		62.5%	12.4%				
Myoutcomes		6.3%		3.0%		45.0%		7.6%		12.2%	21.6%	2.9%			1.4%
Neuroblu			23.9%		4.0%			28.2%		3.9%				4.1%	35.9%
Neuroflow		1.7%			0.9%		4.9%	37.0%	7.2%		23.3%			1.6%	23.4%
NView	21.7%	2.1%			2.0%		5.8%	22.3%	8.8%	7.7%	8.0%		1.0%	2.9%	17.7%
Tridiuum		5.8%		1.6%	0.8%		8.6%	40.1%	4.0%	4.8%	17.4%			0.8%	15.9%
Valant	1.4%	4.5%		50.8%	0.7%		3.9%	7.7%	2.1%	7.2%	15.7%		0.3%	1.1%	4.4%
Blueprint Health	3.0%			9.9%		15.6%		2.9%		34.4%	21.9%	3.0%			9.3%
M3 Information	8.2%							8.2%							83.5%
Nextsteps Solutions		2.9%	0.7%	16.5%	5.2%		17.5%	0.6%	10.9%	3.0%	29.9%		4.3%	4.1%	4.4%
Sivercloud Health		1.7%		0.3%	0.5%		4.7%	30.4%	1.8%	0.3%	24.8%		0.3%	9.2%	26.0%
Horizon Health				23.8%				57.1%	9.6%	9.5%					
Owl Health				7.0%			3.4%	41.4%	10.2%	17.4%	3.4%				17.2%
Vivi Health				5.9%	35.3%			41.1%			11.8%				5.9%
Better Outcomes Now						72.9%				11.7%	3.0%	12.4%			
OQ Measures						6.7%		26.6%		40.0%	6.6%	20.1%			
Ksana Health							4.9%	80.2%	2.5%	2.4%	5.1%			2.5%	2.4%
Greenspace Health								21.2%		74.6%	4.3%				

Figure 4- 8: Dominant Topic by Company

4.6 Topic composition by document type

We explore the proportion of dominant topics within the different document categories. Figure 4-9 is a heatmap highlighting the value of each topic in a document type. We use a Green-Yellow-Red color scale where the higher values tend towards green and lower values towards red. The heatmap indicates that research about MBC-related topics by providers is limited. We anticipated the scarcity of MBC providers' points of view on MBC, specifically BHC hence this study. The prevalence of Therapeutic Alliance in research-related materials indicates MBC providers' desire for collaboration regarding the connection between medical professionals and their patients. Although there is little research published on MBC websites, a proportion of MBC platform themes are covered in every document type. There needs to be more focus on Drug studies, which is understandable because MBCs are essentially into assessing and measuring patient-reported outcomes. We also notice that a segment of each of the 15 topics is published in company Blogs and News pages, which is possible because the two document types are popular means of publicity.

Topic % / Document Type	Community Mental Health	Drug Study	Family and Autism	MBC intake	MBC Platform	Psychometrics	Reimbursement	School-Based Treatment	Substance Abuse	Telehealth	Therapeutic Alliance	Therapy Process	Value-Based Care	Veterans	Integrated healthcare
Blog	6,54%	0,09%	2,30%	1,57%	13,82%	0,28%	19,26%	0,65%	5,16%	2,49%	3,13%	20,37%	6,45%	4,79%	13,09%
News	2,53%	1,69%	7,02%	1,12%	47,47%	0,28%	0,56%	5,90%	1,40%	1,69%	0,56%	10,96%	1,97%	4,21%	12,64%
Research					2,20%	9,89%	7,69%		1,10%		54,95%	2,20%	6,59%	2,20%	13,19%
Company & product info		1,59%	0,79%	4,76%	26,19%	3,97%	15,87%	3,17%		4,76%	4,76%	3,17%	19,84%	1,59%	9,52%
Webinar & podcast			4,00%	4,00%	28,00%		16,00%			8,00%		8,00%	8,00%	4,00%	20,00%
Case study					16,67%		27,78%					22,22%	16,67%	5,56%	11,11%

Figure 4- 8: Topic Composition by document

5 Findings

The use of text analytics has been applied in many research studies for both academic and professional purposes to learn about issues, topics, or themes from a collection of published literature (He et al., 2013; Fang et al., 2018; Hall, Jurafsky, and Manning 2008; Zheng, McLean, and Lu 2006; Piepenbrink and Nurmammadov 2015). However, from our literature review, we have not found studies that used topic modeling approach in MBC.

In this study, we develop a model that identified 15 topics from the insight of MBC providers using the LDA techniques. Based on our assessment of the Coherence and Perplexity measures of the selection stage, we can infer that the 15 topics quantitatively reflect the subject area we are investigating. Further, when the 15 are subjected to the scrutiny of two categories of MBC SME, one from the operations area and the other from Clinicians, there is confirmation of the qualitative reflective aspects of the same models.

The study reveals themes that are closely associated with BHC assessment and diagnosis (e.g., MBC Intake, MBC Platforms, and Psychometrics), efforts to manage BHC (e.g., therapeutic alliance, therapy process, school-based treatment, drug study, and family and autism, integrated behavioral healthcare, and Telehealth), financial management (e.g., VBC and reimbursement), community BH (e.g., veterans, community mental health, school-based treatment, drug study, and family).

5.1 Distribution of topics within documents

As shown in Figure 4-8, we discover that only some topics have the same presence throughout the corpus. The topics: of MBC Platforms, Therapy Process, Reimbursement, Integrated Behavioral Healthcare, and Value-based Care are predominant. MBC providers are sharing information and training on Engagement Patients For Better Outcomes At A Reduced Cost, Increase Patient Intake, and Reduce Financial Risks For Payers. From the perspective of the research objective of trying to reveal insights into low MBC uptake, the prevalence of these topics provides the needed insight into the issues of concerns of the MBC value chain (BHC companies, patients, and payers).

Although the topics of MBC Intake and Psychometrics provide insights into the measures and scales used in MBC, our results indicate that the relevance of the topics in the study could be higher. The irrelevance could be explained from the viewpoint that the measures and scales are standard and, therefore, not candidates for frequent postings or updates. As can be seen, the topics are discussed under the company and product information document category.

The topic Drug Study, which is related to the effectiveness of drugs used in the therapy process, is ranked last in the corpus, which indicates that MBC companies are probably not studying drugs but instead providing outcomes, analyzed by their solutions, to guide research. We propose further research is needed to understand the extent to which MBC outcomes contribute to improving drugs should be investigated.

5.2 Correlations

In general, we observe weak correlations between the topics discussed by the MBC providers. The weakness in correlation is related to the distribution of topics across the entire corpus. We observe that some topics contribute up to 99% to the documents where they are discussed, leaving only 1% for other topics.

The two most negatively correlated topics are MBC Platform versus Therapy Process and MBC Platform versus Reimbursement. The negative correlations point to the need for vendors to emphasize the impact of MBC on reimbursement and therapy process in their content. When companies are talking more about the MBC platform, there are talking less about the therapy process or reimbursement and vice-versa. One example we observe is that solely MBC companies are discussing MBC platform issues (digital technology, innovation, e.t.c.) while EHR companies with integrated MBC are discussing more reimbursement issues (billing, revenue, e.t.c.). With merging MBC technologies and MBC tending towards VBC, we anticipated the conversations to be different on the providers' websites, i.e., the two pairs of topics to be positively correlated.

Strong positive correlations are recognized amongst companies, with more robust positives among companies that provide MBC solutions. Mirah and Greenspace are the strongest positively correlated companies, with a correlation of 0.972, followed by Neuroflow with Tridiuum and Holmusk with Ksana Health. All these companies are MBC companies except Ksana health. In the case of Mirah and Greenspace, for example, the two companies post similar content in the same order of relevance; Value-based Care is the most relevant, followed by the MBC Platform, and finally Therapy Process. When used periodically, the model can provide information on the most pertinent themes to publish about, areas in which they lag, and ways to improve their solutions.

6 Limitations and further research

Any study attempting to distill themes from an extensive literature set has inherent limitations. We take a text-mining technique that assumes the words within the documents can be used to identify the themes discussed within the literature. The underlying assumptions of LDA that we can identify topics by finding the latent distribution of words and topics within the documents leaves us open to potentially finding topics that are nonsensical or not meaningful. To mitigate these limitations, we conduct our analysis by assessing hundreds of LDA model iterations, applying appropriate quantitative measures, evaluating with visualization tools, and incorporating the experience of MBC SMEs. Ideally, these efforts have produced good results, but we must appreciate other possible solutions to such an analysis. We can only offer that the results reasonably represent the topics discussed in the MBC context for BHC. We acknowledge that these results are an excellent foundation to delve deeper into the literature.

The model output is also limited to companies mainly in the US, content published on official company websites but not social media platforms, and text but not video or audio posts. This scope does not include a representation of all MBC companies or postings. For instance, other ways to expand the corpus include exposing additional information from MBC social media pages, extracting video and audio data, and incorporating MBC companies worldwide.

Additionally, given that LDA is a method to turn words into tokens to create matrices for analysis, we focus solely on English language publications to avoid translation challenges. This language constraint means we may miss out on topics captured in non-English research publications not found in our corpus.

The study does not analyze the time trends of the discussions. Such analysis can help to correlate changes in MBC uptake rates with MBC Provider engagement and feedback.

7 Conclusion

In this thesis, we study how MBC service providers are trying to shape MBC adoption within BHC by examining themes from the MBC providers' perspective through applied business analytics and a data science management lens. We apply data science theories and techniques to build and evaluate data-driven methodologies to improve our understanding of MBC service providers' insights.

The data collection phase of this study confirms that many companies are providing MBC for BHC. Most postings from companies whose domain is not MBC fall under MBC platform-related topics. We discovered that behavioral health companies whose specialty is not MBC, for instance, EHRs, have either incorporated or are moving into incorporating MBC into their solutions.

We apply the natural language processing technique of Latent Dirichlet Allocation (LDA) to gain insights into the topics discussed in the MBC service providers domain. This study identifies 15 specific topics from the MBC service providers' websites through our supervised use of LDA. Our modeling approach includes varying key input parameters (e.g., the number of potential topics) to construct hundreds of prospective models. We then use quantitative and qualitative techniques to narrow down to the one model that best fits and identifies a valid and representative breakdown of the discussion.

There is less focus on studying drugs given the lack of majority weighting in the documents for the Drug Study topic. With this apparent lack of studying drugs, we see the justification for further research to understand the extent to which MBC outcomes contribute to improving drugs.

Furthermore, the negative correlation among the topics MBC Platform, Therapy Process, and Reimbursement also justifies further comparative correlation analysis for the different categories of companies.

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9 Appendix