Transforming Mental Health Support: The Role of NLP in Virtual Assistants

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The study investigates the role of Virtual Mental Health Assistants (VMHAs) utilizing Natural Language Processing (NLP) in enhancing patient access, engagement, and support within mental healthcare while addressing ethical considerations surrounding privacy, data security, and efficacy. A bibliometric analysis reveals strengths and limitations in the existing literature, emphasizing deficiencies in corresponding author data and keyword comprehensiveness. The application of Bradford's Law highlights the predominance of select journals in disseminating influential research. Insights into collaboration networks and geographic productivity suggest an evolving global landscape, underscoring the necessity for interdisciplinary approaches to advance VMHA and NLP research.

Keywords: Virtual Mental Health Assistants, Natural Language Processing, Mental Health Care, Bibliometric Analysis, Interdisciplinary Collaboration.

1. Introduction

Technology is integral in today's landscape of global mental health as we face a time when rising need begged that the field think about leapfrogging conventional ways to provide care. Virtual Mental Health Assistants (VMHAs) are a breakthrough in patient engagement Powered by Natural Language Processing, these systems have transformed the way we communicate and support patients providing new and innovative pathways to mental health care. As mental health disorders rise, the demand for timely and reliable support can no longer be adequately addressed with conventional therapeutic tools. Consequently, technology-based interventions have been encouraged to provide ways of engaging and delivering care

The mental health care sector has recently recognized the necessity for cutting-edge approaches to meet the increasing need for accessible and efficient support mechanisms. A notable trend in this area is the emergence of VMHAs, which utilize advanced NLP technology. These digital assistants enable instantaneous communication and tailored interactions between individuals and virtual platforms, helping to fill gaps in conventional mental health services. Such innovations play a crucial role in boosting patient involvement, minimizing obstacles to treatment, and offering immediate assistance, particularly for underserved communities. For example, VMHAs can provide round-the-clock support, decreasing waiting periods for individuals who might otherwise struggle to access traditional mental health resource

Simultaneously, ongoing debates among researchers and practitioners have been sparked by ethical issues related to privacy, data protection, and the effectiveness of AI-based interventions. The development and deployment of VMHAs are significantly influenced by worries about the confidentiality of patient information and the precision of AI-generated responses. To build confidence and ensure patients feel secure when using digital mental health tools, it is crucial to tackle these ethical dilemmas. The incorporation of VMHAs into therapeutic practices offers a promising path for enhancing mental health outcomes and addressing urgent systemic problems in healthcare accessibility, especially as mental health challenges continue to rise worldwide.

2. Review of Literature

The literature review discusses sources of evaluation of the quality and rigour of studies on virtual mental health assistants (VMHAs) and natural language processing (NLP) in mental health. Some of the valuable features for the evaluation are inclusion and exclusion criteria for samples, coding mechanisms, ways to define gold standard, ways to train and assess algorithms, and accurate assessment measures such as recall and precision (Alsawas et al., 2016). Sources of data, data preprocessing, choice of classifiers, programming languages must also be declared in publishable research (Le Glaz et al., 2019). The NLPxMHI framework is designed to help evaluate computational and clinical dimensions such as NLP algorithms, audio features, machine learning pipelines, outcome metrics, and clinical ground truths described by Malgaroli et al. (2023). Also, the researchers ought to assess the linguistic heterogeneity, replicability, and populational shift (Malgaroli et al., 2023). The correspondence between the NLP task-level assessments and the patient or population level clinical outcomes is essential, requiring both intrinsic and extrinsic evaluation approaches (Velupillai et al., 2018).

The study revealed notable gaps in Virtual Mental Health Assistants (VMHAs) regarding their efficacy and user interaction. A primary concern is the lack of transparency and safety in the decision-making processes of VMHAs, which can erode confidence and dependability (Sarkar et al., 2023). There is a crucial need to develop more thorough, secure, and interpretable methods for creating responsible VMHAs that can engage in thoughtful dialogues (Sarkar et al., 2023). Research on the design elements of virtual health assistants indicates that empathy, relational conduct, and self-disclosure have a positive influence on user experience (Curtis et al., 2021). Nevertheless, the existing evidence is diverse and wide-ranging, necessitating more long-term research approaches (Curtis et al., 2021). In the realm of youth mental health interventions via mobile devices, identified gaps include a lack of research in developing nations, limited data on practical feasibility, and the need to tackle issues related to technological and health literacy (Seko et al., 2014).

Bradford's Law, analysed process of distribution of articles across journals in each field, has been extensively studied and validated. This indicate that law holds across various disciplines and search methods, with high correlations observed when fitting regression lines to data sets (Drott & Griffith, 1978). The law reveals a distinct nucleus of high-producing journals and a long tail of less productive ones (Summers, 1983). However, some researchers have raised concerns about the law's limitations, particularly regarding the impact of publication frequency and journal longevity on productivity rankings (Alvarado, 1996). A probabilistic model based on random fragmentation has been proposed to provide a theoretical foundation for Bradford's Law, suggesting that ranking journals inherently yields additional information retrieval benefits (Basu, 1992). Despite its widespread use in collection development and bibliometric analysis, these studies highlight the need for careful consideration of factors influencing journal productivity when applying Bradford's Law.

Natural Language Processing (NLP) and machine learning techniques are considered as a powerful tool for advancing mental health research and practice. These technologies have created a path for analysing unstructured text from various sources, including electronic health records and social media, to gain insights into mental health conditions (Henry et al., 2021). Virtual Mental Health Assistants (VMHAs) leveraging NLP and AI models like ChatGPT supporting mental health professionals and patients to balance emotional hiccups through communication (Sarkar et al., 2023). In the current scenario researchers are exploring causal analysis and perception mining to enhance the interpretability of NLP-based mental health assessments on social media (Garg et al., 2023). While machine learning and NLP offer new paradigms for mental health research, ethical considerations and limitations persist, such as potential biases in data sources and the need for language-specific adaptations (Le Glaz et al., 2019). These technologies provide opportunities to support clinical practice but require assistance to implement the process for further development.

Collaborative patterns in Natural Language Processing (NLP) and related fields reveals gender diversity can optimise gender balance of 5-15% for one gender (Zhang et al., 2023). The study indicates pattern based approaches influencing collaborations among researchers, particularly in genomics (Cagliero et al., 2017). In NLP study observed growing trend towards industry and academia-industry collaborations, which tend to have higher impact compared to purely academic publications (Abuwala et al., 2023). However, network analysis of Vietnamese social scientists reveals sparse connections and high clustering, suggesting inefficient dissemination of knowledge and expertise (Ho et al., 2017). These findings highlight the importance of diverse collaborations and efficient knowledge sharing in advancing research and innovation in NLP and related fields.

Recently the study has identified innovative approaches to form clusters and research communities in scientific literature. Kulkarni et al. (2021) assessed topic based deep contextualized representations for clustering online mental health discourse, while Carniel et al. (2022) applied Transformer Based Models to group topics in interdisciplinary proceedings. Osborne et al. (2014) introduced Temporal Semantic Clustering to identify diachronic research communities on shared research trajectories. Weißer et al. (2020) developed a clustering method using natural language processing and k-means algorithms to filter large article corpora during systematic literature reviews. These studies demonstrate the potential of advanced computational techniques in analysing research communities and topics. By leveraging machine learning, natural language processing, and clustering algorithms, researchers can efficiently identify thematic clusters, track the evolution of research communities, and streamline the literature review process (Kulkarni et al., 2021; Carniel et al., 2022; Osborne et al., 2014; Weißer et al., 2020).

Research on virtual mental health assistants (VMHAs) and natural language processing (NLP) observed increase in international collaboration and geographic diversity in authorship. While the United States has historically dominated mental health study as its share decreased from 60% to 42% between 1980 and 2011, whereas the European Union's share grew from 27% to 40% (Larivière et al., 2013). International collaborations in mental health research increased significantly, from 3% in 1980 to 22% in 2011 (Larivière et al., 2013). However, authors from other geographic areas remain underrepresented (Minas et al., 2014). Efforts to promote collaborative writing between low-, middle- and high-income country researchers have been recommended to ensure more diverse, ethical, and contextually relevant publications (Kohrt et al., 2014). Recent studies using machine learning and NLP in mental health have primarily relied on medical records and social media data, with most research conducted using Python (Le Glaz et al., 2019).

The geographical distribution of corresponding authors and mental health resources shows significant disparities across regions. High income countries focus more on mental health research, whereas authors from Africa, Latin America, the Caribbean, and the Middle East are in stage of decline (Yalçın et al., 2022). In the United States, mental health treatment facilities are more predominant in low-income communities, while office-based practices of mental health professionals are concentrated in higher income areas (Cummings et al., 2017). However, individuals diagnosed with severe mental illness in Philadelphia had better access to community resources compared to the general population (Metraux et al., 2012). Geographical perspectives can provide valuable insights into the spatial patterns of mental health issues and service distribution at various scales (Jones, 2001). These findings highlight the importance of considering geographical factors in mental health research and policy-making to address disparities in resource availability and accessibility across different regions.

Over the past decade, research on Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP) predominantly carried out to explored the use of NLP techniques. This leads to analyse trends in telepsychology literature, particularly in response to the COVID-19 pandemic (Conroy et al., n.d.). The usage of NLP application in digital services has gained prominence, with a focus on machine learning and deep learning (Díaz Tunjar, 2023). The study indicates that researchers have utilized machine learning and NLP methods to analyse medical records and social media data, aiming to improve mental health diagnosis and treatment (Le Glaz et al., 2019). Recent work has emphasized the need for more comprehensive, safe, and explainable VMHAs, highlighting the importance of contextual knowledge and trustworthiness in patient interactions (Sarkar et al., 2023). These studies reflect a shift towards developing more sophisticated, ethical, and clinically relevant NLP tools for mental health support and research.

The study highlights integration of artificial intelligence (AI) and machine learning (ML) in mental healthcare. These technologies helping the health industry to detect the symptoms of mental health disorders in an early stage, personalized treatment planning, and AI-driven virtual therapy (Olawade et al., 2024). An integrated framework combining unsupervised learning and natural language processing (NLP) techniques has been proposed for analysing digital healthcare data, potentially leading to betterment of patient outcomes and personalized treatments (Shastry, 2024). However, the development of effective machine leaning applications in mental health faces complex challenges. A systematic review of current machine leaning work in mental health emphasizes the need for stronger integration of human centred and multi-disciplinary approaches in research and development. It also calls for greater consideration of the personal, social, and ethical implications of machine learning models and interventions in real world mental health contexts (Thieme et al., 2020). These studies emphasize the transformative potential of artificial intelligence in mental healthcare while highlighting the importance of responsible and ethical implementation.

3. Research Gap Analysis

Table

Article Title	Variable(s)	Gap Identified	Gap Description	Citation
Criteria for Evaluating Quality in VMHA and NLP Studies	Evaluation Criteria, Methodology	Limited Scope in Evaluation Metrics	Need for broader evaluation metrics beyond recall and precision to assess overall effectiveness and clinical impact in mental health applications.	Alsawas et al., 2016
The NLPxMHI Framework for Assessing VMHAs	NLP Algorithms, Clinical Metrics	Underexplored Linguistic Diversity	Limited research addressing linguistic diversity and population biases, impacting the applicability of VMHAs in diverse cultural contexts.	Malgaroli et al., 2023
Explainability and Safety in VMHAs	Explainability, Safety	Lack of Explainability in VMHA Models	Insufficient research on developing transparent, safe VMHAs, impacting user trust and engagement in therapeutic contexts.	Sarkar et al., 2023
Design Characteristics and User Experience in VMHAs	Empathy, Self-Disclosure	Need for Longitudinal Studies	Few studies using longitudinal designs to assess long-term effects of empathy and self-disclosure on user experience in VMHAs.	Curtis et al., 2021
Youth Mental Health Interventions via Mobile	Feasibility, Technical Literacy	Gaps in Low/Middle-Income Countries	Limited data on the feasibility of mobile interventions in low- and middle-income countries and how technical/health literacy affects accessibility and outcomes.	Seko et al., 2014
Bradford's Law Application in Bibliometric Analysis	Journal Productivity, Article Distribution	Productivity Influences	Need for further examination of publication frequency and journal longevity in productivity rankings to ensure accurate bibliometric analysis.	Alvarado, 1996
NLP and Machine Learning in Mental Health Research	NLP Techniques, Data Sources	Bias and Language Adaptation	Ethical concerns persist regarding biases in data sources and lack of language-specific NLP adaptations, affecting the reliability of mental health analysis.	Le Glaz et al., 2019
Collaborative Patterns in NLP Research	Gender Diversity, Collaboration	Need for Diverse Collaboration Models	Insufficient research on the impact of diverse gender and international collaborations, especially in regions with sparse connections, for effective knowledge exchange.	Zhang et al., 2023
Innovative Approaches for Thematic Clustering in Mental Health	Clustering, Topic Modeling	Limited Thematic Identification	Need for methods that can identify thematic clusters and track evolution in VMHA and NLP research to understand emerging trends and research community networks.	Kulkarni et al., 2021; Carniel et al., 2022
Geographic Distribution of Research in Mental Health	Geographic Distribution	Underrepresentation in Low-Income Areas	Lack of representation of authors from lower-income regions, which affects the contextual relevance and inclusivity of mental health research findings.	Minas et al., 2014; Kohrt et al., 2014
Advancements in NLP During the COVID-19 Pandemic	Telepsychology, Digital Services	Shift Towards Explainable AI	Emphasis on need for explainable and trustworthy VMHAs to support patient interactions effectively, especially in high-demand telehealth contexts.	Conroy et al., n.d.; Sarkar et al., 2023
AI and ML in Early Detection and Personalized Mental Health	Early Detection, Personalization	Integration of Human-Centered Approach	Greater emphasis needed on human-centered, multidisciplinary approaches to address ethical implications of AI in real-world mental health applications.	Thieme et al., 2020

The table provides a structured analysis of research gaps in the fields of Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP). Key findings indicate the need for broader evaluation metrics in VMHA studies, moving beyond basic accuracy measures to assess clinical effectiveness. Research lacks focus on linguistic diversity and population biases, affecting the applicability of VMHAs in multicultural settings. Additionally, studies often overlook explainability and safety in VMHA decision-making, which can impact user trust and therapeutic engagement.

Further, the user experience with VMHAs could benefit from longitudinal research, particularly in exploring empathy and self-disclosure effects. In mobile mental health interventions, there is limited data on feasibility in low- and middle-income countries, as well as on overcoming technical and health literacy barriers. Bibliometric analysis reveals the need to examine factors influencing journal productivity, while NLP in mental health still grapples with ethical concerns around data bias and the lack of language-specific adaptations.

Collaborative research in NLP would benefit from greater gender and geographic diversity to ensure effective knowledge exchange, especially in underrepresented regions. Thematic clustering methods are also underdeveloped, limiting insights into emerging trends. Lastly, AI and machine learning applications in mental health underscore the need for responsible, human-centered approaches to address the social and ethical implications of these technologies in real-world settings.

4. Objectives of the study

The primary objectives of this study are:

1. To assess the quality of the literature dataset related to Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP), identifying strengths and gaps in available data;
2. To analyse the distribution and impact of scholarly articles across various sources using bibliometric measures such as Bradford's Law and h-index;
3. To explore the author collaboration network and the thematic clustering of research communities contributing to the fields of VMHAs and NLP;
4. To evaluate the geographical distribution of corresponding authors to understand international research collaboration trends; and
5. To analyse evolving trends in keywords and topics over time to identify emerging research areas and their implications for future studies

5. Methodology

The present study adopts a bibliometric analysis, applying quantitative metrics to review the literature on VMHAs and NLP. Data was collected from Scopus databases to give a more comprehensive picture of scholarly output related to bibliometrics information, author affiliations, and citation counts, using network analysis techniques for visualization of author collaboration. To have depth insight on the study Bradford's laws of scatter, were used to identify core sources with their contribution towards publication. A h-index metric enabled the identification of the impact of various journals and authors. This was complemented by looking into geographic distribution, while collaboration among countries was visualized. Keyword trend analysis along with thematic mapping was employed to study how research topics have changed over time, thus providing a better understanding of the evolution in this field.

6. Results and Discussions

6.1 Quality Assessment of The Literature Dataset

Metadata	Description	Missing Counts	Missing %	Status
AB	Abstract	0	0.00	Excellent
DT	Document Type	0	0.00	Excellent
SO	Journal	0	0.00	Excellent
LA	Language	0	0.00	Excellent
PY	Publication Year	0	0.00	Excellent
TI	Title	0	0.00	Excellent
TC	Total Citation	0	0.00	Excellent
AU	Author	7	2.87	Good
C1	Affiliation	11	4.51	Good
DI	DOI	18	7.38	Good
DE	Keywords	115	47.13	Poor
ID	Keywords Plus	139	56.97	Critical
RP	Corresponding Author	144	59.02	Critical
CR	Cited References	244	100.00	Completely missing
WC	Science Categories	244	100.00	Completely missing

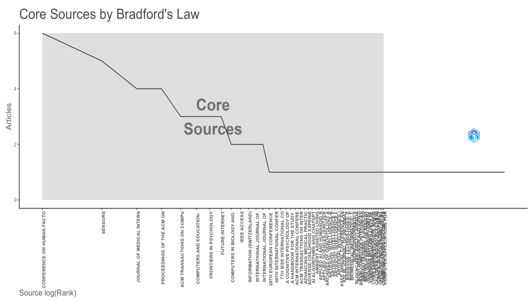
The quality assessment of the literature dataset scrutinizes several advantages and major limitations, which require attention in the course of literature evaluation. Most importantly, all papers are complete in bibliometric information with abstracts, titles, publication years, document types, journal information, language, and total citation counts presented. Their relatively strong position allows for further dissecting the assumptions referring to the essence and implications of studying virtual mental health assistants. Moreover, author details, institution details, and DOIs are quite reasonably available, at the rates of 97.13%; 95.49% and 92.62% respectively to allow adequate author network analysis and organization affiliation mapping.

However, there are several gaps that are critical which may limit the range of analysis. Contact details of the corresponding authors are not available for about 59.02 % of the papers which makes future possible cooperative work or explanation of some findings difficult. Still, there are the significant gaps in keyword data: regular keywords are missing in 47,13% of articles and Keywords Plus – in 56,97%. These are some of the issues arising from such omissions when undertaking thematic analysis; extrapolating research trends; and locating the intersection of natural language processing and mental health support. There are also completely blank sections, these include: specified references and sciences for citation, these make citation network analysis, flow of knowledge and identification of the influential papers challenging.

Regarding these limitations, the literature review should use the full database of abstracts for content analysis where the publication years should be used to follow the development of virtual mental health assistants. There is more that can be done with the current affiliation data to understand more about institutional collaboration. Secondary techniques could involve manually extracting missed out on keywords from the abstracts, and possibly consider third party tools for science classification. In addition, combining Scopus with other databases, for example, Web of Science or Pub Med could improve the identification of complete reference information. There are acknowledged limitations in the use of the current dataset to conduct citation network and keyword trending and the missing data in achieving corresponding authors may limit targeted contact with important researchers.

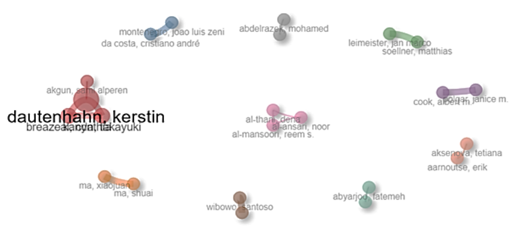
Taking into consideration the improvement of documentation enhancement, it would be useful to build a supplementary keyword framework with the help of abstraction analysis and the categorization developed from the content of abstracts. Moreover, if possible, an enhanced extraction of associated reference from the full text source may help increase the sample size. In conclusion, the scales adopted herein for the metadata quality assessment highlight a critical need for further research into abstracts and titles and careful caution when making quality assessments based on keywords and citations. A more fundamental bibliometric assessment of the topic is, however, still possible due to the comprehensive accessibility of core bibliometric data on the subject of V-MHAs and NLP in patient interactions.

Analysis of core sources by Bradford’s Law



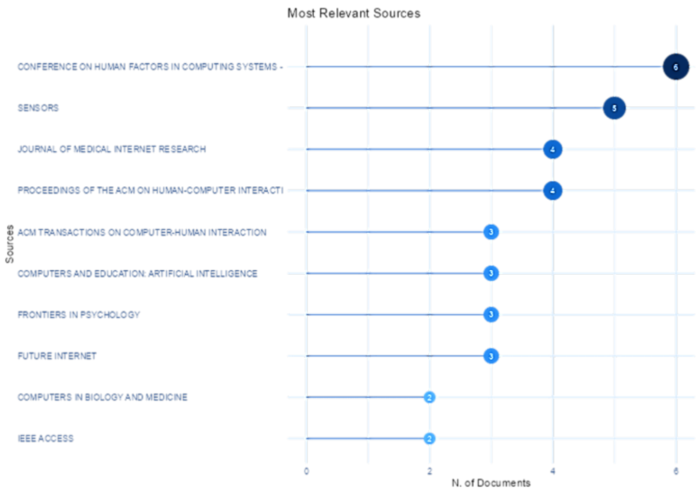
Bradford's Law, a foundational principle in information science, suggests that a small number of core journals or sources contribute disproportionately to the literature on a given topic. In this plot, which applies Bradford's Law to the fields of Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP), the distribution of relevant publications across sources reveals several distinct zones. The sharp initial decline indicates that a select few core sources, likely highly influential, contribute the majority of pertinent articles. Moving rightward, the curve flattens, illustrating a dispersion zone where a greater number of sources provide fewer articles each, expanding the breadth of literature distribution. Finally, the nearly horizontal tail represents numerous sources with minimal contributions, reflecting a wide but sparse distribution of relevant publications across the field.

Analysis of Author Collaboration Network



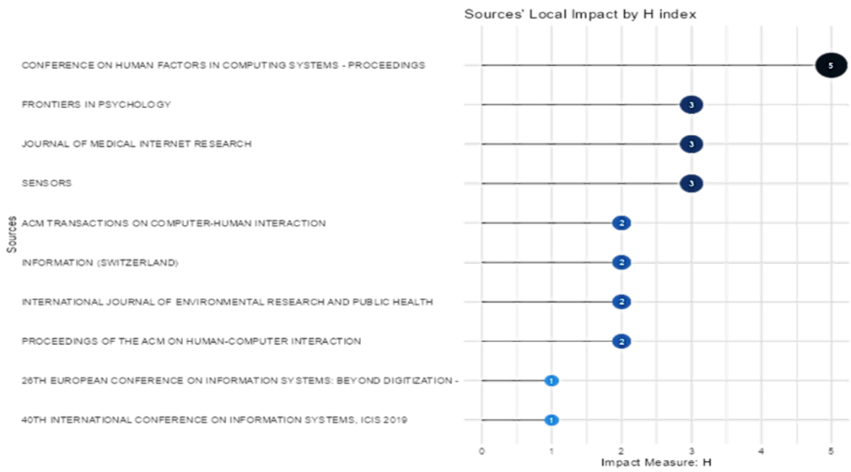
The clustering analysis of authors engaged in research on Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP) reveals the presence of distinct research communities, each contributing unique perspectives to the field. Cluster 1, led by Kerstin Dautenhahn, centers on broader themes of human-robot interaction and social robotics, with a particular focus on mental health and well-being. In contrast, Cluster 2, associated with Alperen Akguna, emphasizes the technical dimensions of NLP, particularly its application in VMHAs concerning natural language understanding and generation. Cluster 3, represented by Jan Leimeister, appears to be concentrated on the design and development of VMHAs, prioritizing user experience and interaction design. Meanwhile, Cluster 4, led by Janice M. Cook, explores the clinical and ethical implications of employing VMHAs in mental health care settings. Cluster 5, associated with Tatiana Aksepova, focuses on utilizing NLP to analyze and understand human language, potentially informing the functionality of VMHAs. Cluster 6, represented by Fatemeh Abayneh, investigates the use of NLP for generating natural language responses within VMHAs. Finally, Cluster 7, led by Antoso Wibowo, examines the application of VMHAs in specific cultural or linguistic contexts.

Document Distribution on VMHAs and NLP Across Sources



The dot plot illustrates the distribution of documents published across various sources on Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP). Each dot represents a source, positioned along the x-axis based on its publication volume. Key insights highlight that sources like the *Conference on Human Factors in Computing Systems* and *Sensors* hold high publication counts, signaling their substantial relevance and influence within VMHA and NLP research. The distribution pattern shows that while literature is spread across numerous sources, a moderate clustering effect exists, with a core group of sources contributing a significant portion of the field's output. This clustering indicates a concentrated base of literature from prominent contributors, supporting the dissemination and expansion of VMHA and NLP research across related disciplines.

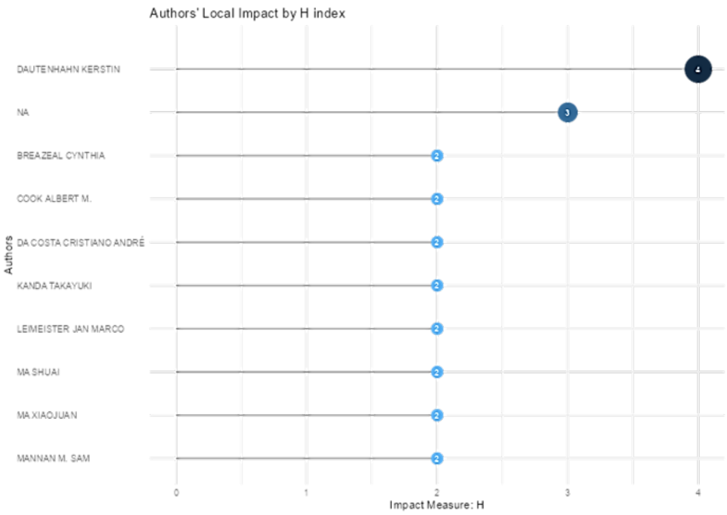
Analyses of Source Impact on VMHAs and NLP Using h-Index



The dot plot effectively visualizes the "local impact" of various sources in the domain of Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP) as measured by the h-index, a metric that reflects both the quantity and citation impact of published articles.

Key observations from the plot highlight several important trends. First, the sources exhibiting the highest h-index values include the "Conference on Human Factors in Computing Systems - Proceedings" and "Frontiers in Psychology," indicating that these publications have made a significant impact in the field, characterized by a high concentration of highly cited articles. The spread of dots across a range of h-index values further suggests that relevant literature is distributed among sources with varying levels of impact, illustrating a diverse research landscape. Additionally, there is a noticeable clustering of sources with moderate h-index values, implying that while they contribute significantly to the field, their overall impact is somewhat lower compared to the top sources.

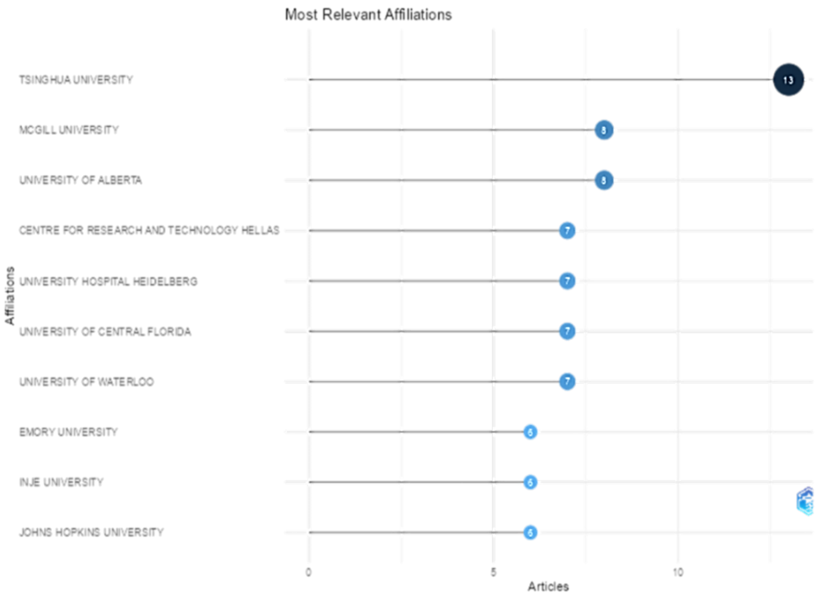
Assess Research Impact: H-Index as a Measure of Productivity and Citation



The H-index is a widely recognized metric for assessing the impact of a researcher's body of published work. Defined as the number of publications (h) that have each received at least h citations, the H-index provides a balanced measure of both productivity and citation impact. A higher H-index generally reflects a more substantial influence on the field, as it indicates that the researcher has produced multiple works that are frequently cited by other scholars.

The accompanying graph displays the H-index for several authors contributing to the fields of Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP). Notably, Kerstin Dautenhahn stands out with the highest H-index, highlighting their extensive influence and the widespread citation of their work. Other researchers demonstrate H-indices in the range of 2-3, reflecting moderate influence; their contributions have been cited reasonably but do not match the citation frequency of the top-ranking author. Some authors show lower H-indices, which may suggest that their research is either relatively recent or has not yet garnered as many citations as others in the field.

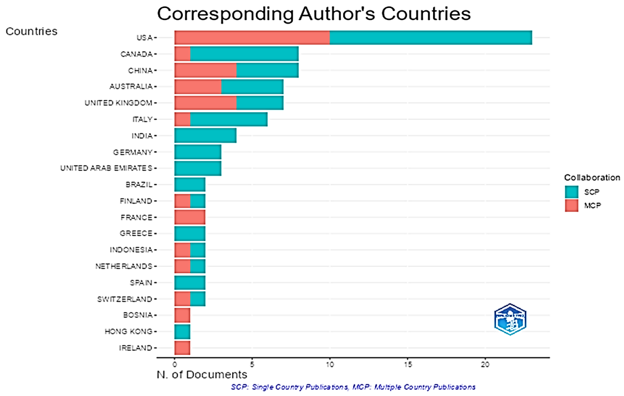
Analysis of Research Productivity in VMHAs and NLP Across Institutions



This dot plot provides a visual representation of research productivity in Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP), based on the number of articles published by researchers across various institutions. Tsinghua University emerges as the most prolific institution, with 13 published articles, underscoring its prominent research role in the field. Following closely are McGill University and the University of Alberta, with 9 and 8 publications, respectively. Additional notable contributors include the Centre for Research and Technology Hellas, University Hospital

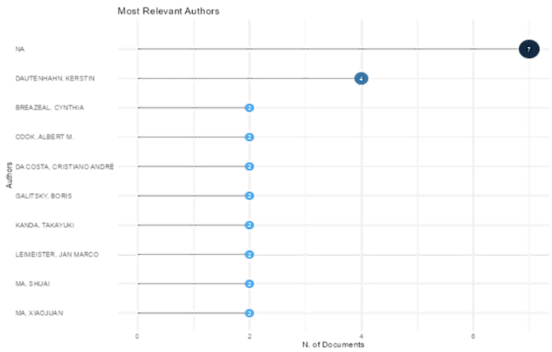
Heidelberg, and the University of Central Florida. A group of institutions, each with approximately 7 articles, further reflects a moderate level of research activity in VMHAs and NLP.

Geographic Distribution of Corresponding Authors in VMHAs and NLP: Single-Country Publications (SCP) vs. Multiple-country publications (MCP)



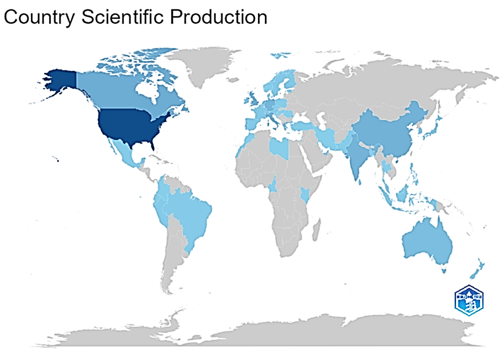
This stacked bar chart illustrates the geographic distribution of corresponding authors for research on Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP), distinguishing between single-country publications (SCP) and multiple-country publications (MCP). The data shows a notable dominance by the United States, which has the highest number of corresponding authors, reflecting a robust research presence and contributions across both SCP and MCP formats. This suggests that the US is a central player in VMHA and NLP research. Additionally, the chart underscores the role of global collaboration, with countries such as Canada, China, and Australia contributing significantly through multiple-country publications. A diverse array of countries, including India, Brazil, and the United Arab Emirates, also feature prominently, highlighting the broad geographic representation in this field.

Analyses of Publication Counts Among Leading Authors in VMHAs and NLP



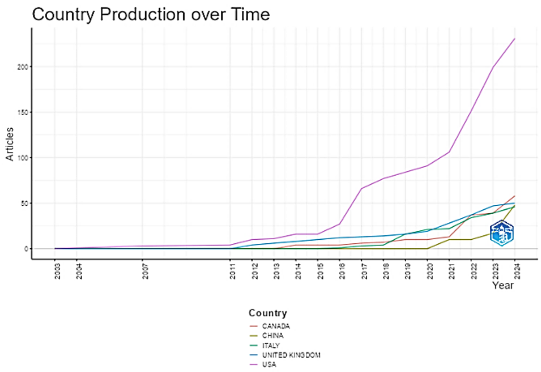
This dot plot presents the publication counts of the most active authors in the field of Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP). Dautenhahn, Kerstin stands out as the most prolific author with 7 publications, highlighting a substantial contribution and established presence in the field. Several other authors with 2-3 publications demonstrate a moderate level of research engagement, suggesting ongoing or focused work in VMHAs and NLP. Meanwhile, a few authors with a single publication may represent emerging researchers or those with a narrower focus on this area.

World Map Visualization of Scientific Output in VMHAs and NLP



The world map provides a detailed visualization of scientific output in the fields of Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP), with color intensity signifying the extent of each country's research contributions. Notably, North America and Europe, particularly the United States, the United Kingdom, Germany, and France, are shaded in the darkest hues, emphasizing their substantial role in advancing research in these areas. This dominance underscores a strong research infrastructure and focus in these regions, which leads global scientific contributions. Meanwhile, countries such as Canada, Australia, and China are represented in darker shades, suggesting their increasing involvement and emergence as important research hubs in VMHA and NLP studies. Additionally, the distribution of research activity across countries of varied levels of scientific output suggests significant global collaboration in the field.

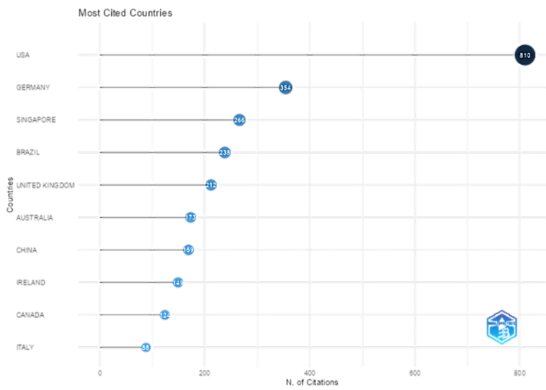
Cumulative Article Publication Trends in VMHAs and NLP Over Time



This line graph illustrates the cumulative number of published articles over time in the fields of Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP), across multiple countries. It provides insight into the growth trajectory and evolution of research activity in these areas globally.

A closer look at the data reveals notable variations in growth patterns among countries. For instance, while the United States and Canada have consistently contributed publications over the years, there has been a more recent surge in research activity from China and Italy, indicating a new wave of interest and investment in VMHA and NLP research in these regions. The United States has maintained its position as a dominant leader in this field, showing a steady and consistent increase in the number of published articles. Meanwhile, China and Italy have emerged as significant research hubs, particularly in recent years, signifying these countries' expanding role in advancing research and development in VMHAs and NLP. Overall, the cumulative trend across countries reflects an accelerated growth rate, especially in recent years, suggesting heightened research interest and activity in these fields.

Analyses of Total Citations by Country in VMHAs and NLP Research



This dot plot provides an overview of the total citations accrued by research outputs from various countries in the fields of Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP). Each country's total citations reflect its research impact and prominence within these fields.

Notably, the USA stands out with a significantly higher number of citations, underscoring its dominant role in advancing VMHA and NLP research and its substantial influence on the field. European countries, particularly Germany, the UK, and Ireland, also display high citation counts, indicating a robust contribution from European research institutions. Additionally, countries such as Singapore, Brazil, Australia, and China are emerging as notable contributors, marked by a growing number of highly cited publications, suggesting these regions are increasingly recognized as influential research hubs. Overall, the dot plot reveals a geographically diverse set of contributors, underscoring the global nature of VMHA and NLP research and the broad-based interest in advancing these fields.

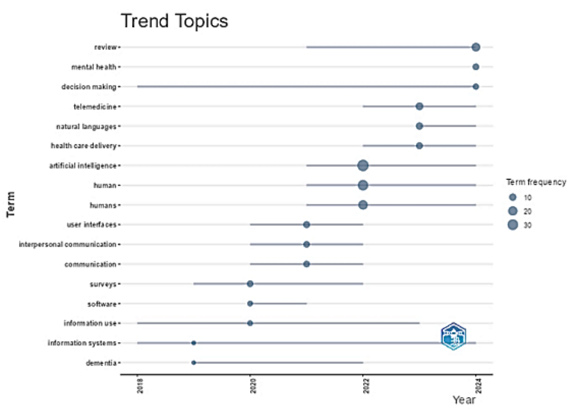
Analyses of Word Cloud of Key Themes in VMHAs and NLP Research Literature

This word cloud visualizes the prevalence of terms within Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP) literature, highlighting dominant themes in the field. Central terms like "artificial intelligence" emphasize AI's crucial role in advancing VMHA functionalities. Notably, terms such as "human," "human-computer interaction," and "user interfaces" reflect a strong focus on human-centered design, underscoring the importance of accessibility and responsiveness in VMHAs. The prominence of "natural language processing" and related terms reaffirms NLP as a foundational technology, enabling VMHAs to comprehend and generate human language. Additionally, terms like "mental health," "health care," and "patient care" point to VMHAs' significant applications in mental health support, illustrating the field's commitment to enhancing well-being. Words like "technology," "automation," "machine learning," and "deep learning" underscore the reliance on cutting-edge technologies to refine and expand VMHA capabilities.

Treemap Visualization of Hierarchical Themes in VMHAs and NLP

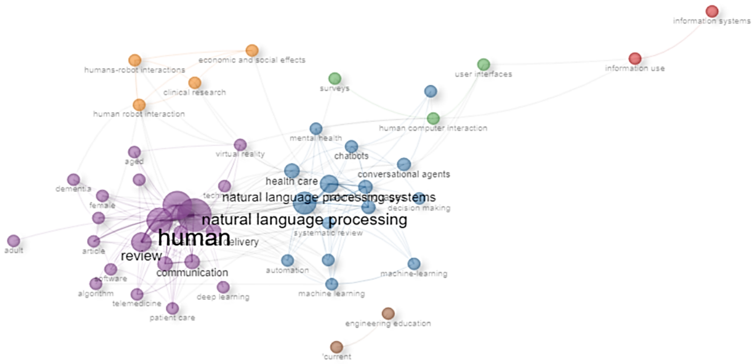
A tree map visualization reveals hierarchical themes central to Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP), delineating foundational elements within this research domain. The largest segment, representing Artificial Intelligence (AI), highlights its critical role as the foundational driver for VMHA and NLP advancements. NLP occupies a substantial area, reflecting its essential function in enabling VMHAs to interpret and interact with human users. Human-centered design principles are underscored by the prominence of Human-Computer Interaction (HCI) themes, with keywords like "interaction," "user interfaces," and "humans" signaling the emphasis on accessibility and usability. Mental Health and Health Care are also central themes, indicating primary applications of VMHAs in supporting mental health and patient care. Complementing these core themes, terms related to Technology and Automation—such as "machine learning," "deep learning," and "automation"—suggest the technological innovations propelling VMHA development.

Analysing Evolving Trends in Keywords and Topics in VMHAs and NLP



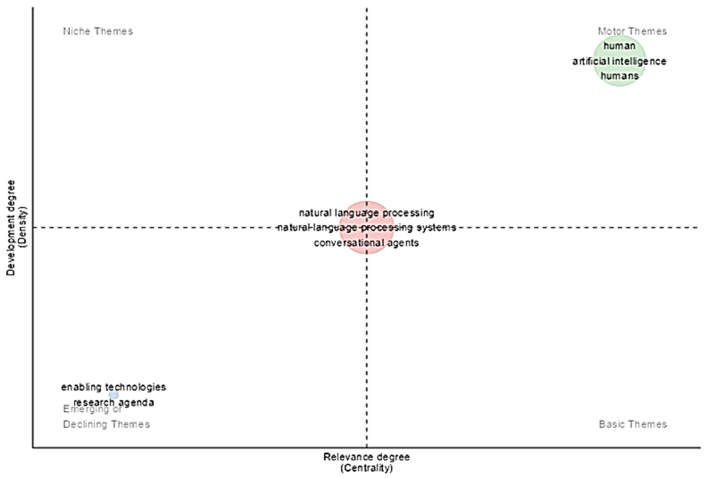
This dot plot illustrates the evolving trends of specific keywords and topics in Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP) research, providing insights into how focus areas within the field have shifted over time. A general pattern of steady growth across most keywords reflects increasing interest and active research engagement. Particularly, keywords like "telemedicine" and "interpersonal communication" have shown notable rises in recent years, highlighting an emphasis on practical applications and user-centered approaches within VMHAs. Core concepts, including "artificial intelligence," "human-computer interaction," and "natural languages," have maintained consistent relevance, underscoring their foundational role in enabling and advancing VMHA and NLP research.

Global Network Representation of Keyword Interrelationships in VMHAs and NLP



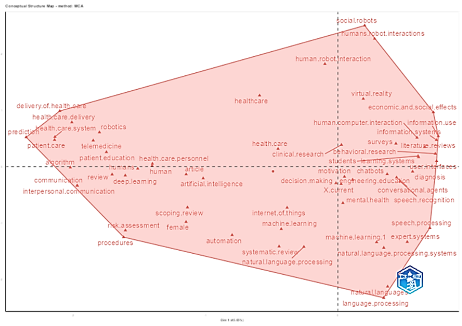
This network visualization provides a comprehensive mapping of the interrelationships among keywords in Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP) research, where nodes represent keywords and edges signify the connections between them. Node size indicates keyword frequency, while edge color and thickness reflect relationship strength. Key insights highlight central themes, with pivotal nodes such as "human," "natural language processing," and "health care" linking extensively to other keywords, underscoring their foundational role. The network also emphasizes VMHA and NLP research's interdisciplinary scope, with connections to fields like computer science, psychology, linguistics, and healthcare. Keywords such as "chatbots," "conversational agents," and "telemedicine" reveal a growing focus on applied VMHA solutions, while terms like "review," "systematic review," and "clinical research" indicate an emphasis on rigorous, methodological approaches within this domain.

Thematic Map Analysis: Visualizing Development and Relevance in VMHAs and NLP



This thematic map visually represents the development and relevance of key themes in the field of Virtual Mental Health Assistants (VMHAs) and Natural Language Processing (NLP). The x-axis denotes thematic relevance (centrality), while the y-axis indicates thematic development (density). Core themes, including "human," "artificial intelligence," and "natural language processing," appear in the top-right quadrant, reflecting their high relevance and advanced development as foundational elements driving research in VMHAs and NLP. Emerging themes, such as "natural language processing systems" and "conversational agents," occupy the top-left quadrant, signifying their growth potential and anticipated future significance. Declining themes like "enabling technologies" and "research agenda" are situated in the bottom-left, suggesting diminishing relevance as the field evolves. Additionally, specialized "motor" and "niche" themes in the top-right quadrant represent high-relevance areas with limited development, highlighting promising avenues for further research.

Conceptual Structure Map: Visualizing Relationships in VMHAs and NLP



The Conceptual Structure Map (CSM) reveal several critical insights. First, the core themes of "human," "artificial intelligence," and "natural language processing" emerge prominently, underscoring their fundamental role in shaping the landscape of VMHA and NLP research. Furthermore, the interdisciplinary nature of this field is evident, as the map showcases connections to diverse areas such as psychology, computer science, and healthcare, reflecting the collaborative efforts necessary to advance the development of VMHAs. The inclusion of concepts like "chatbots," "conversational agents," and "telemedicine" highlights emerging trends, indicating a rising interest in practical applications that leverage these technologies to enhance mental health care. Additionally, the emphasis on rigorous methodologies, as denoted by keywords such as "review," "systematic review," and "clinical research," signals a commitment to high standards of research integrity and validity.

7. Conclusions

The integration of Virtual Mental Health Assistants (VMHAs) into mental health care signifies a transformative shift in how support is delivered to individuals in need. From a societal perspective, the findings underscore the potential of VMHAs to enhance access to mental health resources, particularly for underserved populations. By providing timely and personalized support, these technologies can bridge existing gaps in care and promote mental well-being. However, the ethical concerns surrounding privacy and data security remain paramount, necessitating ongoing dialogue and vigilance to build user trust and ensure responsible technology deployment.

In terms of research implications, the study highlights the necessity for comprehensive bibliometric analyses that encompass complete author information and keyword data. Addressing these gaps will facilitate a more nuanced understanding of the VMHA and NLP landscape, enabling more effective thematic analyses and fostering collaborative efforts across disciplines. Future research should prioritize interdisciplinary collaboration among computer scientists, psychologists, and healthcare professionals to enhance the design and functionality of VMHAs. Additionally, clinical validation studies are critical to assessing the practical impact of VMHAs on mental health outcomes, ensuring that these technologies deliver real-world benefits.

From a managerial perspective, organizations looking to implement VMHAs must prioritize ethical considerations in their deployment, investing in staff training to ensure practitioners are well-equipped to utilize these tools effectively. Promoting international collaborations can enrich the research landscape, leveraging diverse insights and expertise to improve VMHA development and application.

Theoretically, this study contributes to a deeper understanding of the intersection between VMHAs and NLP within the mental health care framework. Future research directions should explore the dynamic nature of keyword trends, particularly those related to telemedicine and interpersonal communication, as these themes evolve with the growing integration of technology in mental health. By addressing these multifaceted implications and fostering collaborative efforts, the field can progress toward developing innovative, effective solutions that significantly enhance mental health support and outcomes.

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