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Application OF Topic Modeling and Data Visualization in Libraries: A Review of Literature

Ranjan Borah * and Margam Madhusudhan**

**Research Scholar, Department of Library and Information Science, University of Delhi, Delhi-110007, India*
Email: ranjanborah87@gmail.com;
ORCID: https://orcid.org/0000-0002-0913-2267
*** Professor, Department of Library and Information Science, University of Delhi, Delhi-110007, India*
Email: madhumargam@gmail.com;
ORCID: https://orcid.org/0009-0004-3412-0526

ABSTRACT

This study explores the evolving role of topic modeling and data visualization within Library and Information Science (LIS), focusing on their theoretical underpinnings, practical applications, and recent research trends. To clearly understand the techniques, 73 scholarly publications, published between 2003 24, were retrieved from different databases such as Scopus, Web of Science, LISA, and Google Scholar. A detailed review of the literature of the publications was done to understand the theoretical aspects of the techniques and their prospects. Topic modeling is a sophisticated text-mining technique that can be done using a variety of algorithms such as LDA, STM etc., each one suited to different types of datasets and research objectives, with diverse applications in libraries such as Enhancing Information Retrieval and Search Systems, Improving Digital Library Services, Document Clustering and Recommendation Systems, Subject Metadata and Multimedia Libraries, Topic Trends and Knowledge Discovery in LIS etc.

Analytical findings of the publications reveal that 75% of the literature emerged in the past decade, with a notable concentration between 2018 and 2022, indicating heightened academic interest in these data-driven methodologies. The reviewed documents include journal articles (70%), conference papers (18%), book chapters (9%), and theses (3%), highlighting diverse scholarly contributions. Topic modeling techniques, particularly Latent Dirichlet Allocation (LDA), are recognized for uncovering hidden patterns in large text corpora, while data visualization translates complex datasets into impactful visuals. Together, these tools offer immense value to LIS professionals, data analysts, and researchers seeking to advance knowledge discovery, improve decision-making, and enhance scholarly communication in modern libraries.

Keywords: Topic Modeling, Latent Dirichlet Algorithm, Data visualization, Library, Librarian

*Corresponding Author

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1. INTRODUCTION

The insatiable human curiosity for knowledge, coupled with the rapid generation of ideas, development of digital resources, and advancement in research infrastructure, has led to an unprecedented explosion of data. Managing, organizing, and making sense of this vast and complex information, spanning countless disciplines, has become a formidable challenge for libraries and information centres. These institutions are increasingly adopting computational methods powered by algorithms, intelligent systems, and specialized applications to effectively curate, interpret, and analyze large datasets.

The most promising techniques are topic modeling, text mining, journal mapping, authorship network analysis, and data visualization. These techniques have evolved over the last two decades, and extensive research on these topics is being carried out across different levels and domains. Since these techniques are widely used across different fields and research subjects, and are constantly evolving in scope and in terms of usability and acceptability, the study has been conducted to clearly understand the current state of topic modeling and various data visualization techniques. Library and Information Science is one such domain where new ideas are constantly incorporated and tested to ensure the smooth functioning and benefits of information centers, enabling them to work efficiently for their users. Analyzing the metadata of relevant scholarly documents aims to provide a comprehensive literature review and demonstrate how topic modeling can be effectively leveraged to enhance library services and information discovery. It will help to understand how these innovative tools can enable libraries to deliver more precise, user-centered information services and transform raw data into actionable insights.

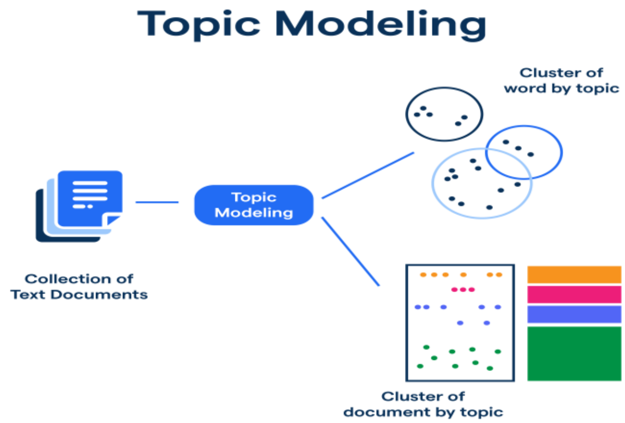

Figure 1: Image depicting the process of Topic Modeling

2. METHODOLOGY

The study is undertaken to understand the various hidden concepts related to topic modeling clearly, the algorithms used for topic modeling, how to use visualization techniques to visualize relevant information, and to explore the application and relevance of topic modeling and data visualization within the library and information science domain.

Since the study is related to topic modeling and use of visualization of data, searches were carried out across multiple academic databases and scholarly platforms, including Library and Information Science Abstracts (LISA), Scopus, Web of Science, Emerald Insight, and Google Scholar, in addition to ResearchGate and publisher-specific e-journal websites by using targeted keyword combinations such as "topic model", "LDA" (Latent Dirichlet Allocation), "STM" (Structural Topic Model), "data visualization", and "topic modelling in libraries" to retrieve relevant literature. 89 documents were identified as potentially relevant to the study from an initial pool of 200+ documents. After a detailed screening for quality, scope, and relevance to the research objectives, 73 documents published between 2003 and 2024 were selected for in-depth analysis.

The detailed review of the literature on topic modeling and data visualization was conducted separately to clarify the key concepts. Their potential use and prospects in libraries were also studied. The selected corpus was examined in RStudio using R to conduct bibliometric and content-based analyses. The theoretical approach enabled qualitative understanding of the relevant topics and trends, and the analytical approach enabled quantitative and thematic visualization of the field's trends, authorship patterns, and topic evolution.

3. TOPIC MODELING (TM)

Topic modeling is a powerful text-mining technique to uncover hidden thematic structures within large collections of unstructured documents. It works by analyzing patterns in word usage and grouping frequently co-occurring terms into distinct topics, thus enabling researchers to identify dominant themes across vast datasets. This technique facilitates the organization and interpretation of complex textual information and enhances the generation of meaningful insights.

At its core, topic modeling relies on probabilistic models that process textual data to extract coherent topics, offering a structured representation of unstructured content. As Blei (2012) explains, "Topic models are algorithms for discovering the main themes that pervade a large and otherwise unstructured collection of documents and can organize the collection according to the discovered themes. Topic modeling algorithms can be applied to massive collections of documents and can be adapted to many kinds of data. They can find patterns in genetic data, images, and social networks, among other applications."

In research contexts, topic modeling is a valuable tool for tracking evolving trends, identifying emerging areas, and discovering new fields of inquiry. As Lamba and Madhusudhan (2019) noted, "Topic modeling not only helps the researcher to determine the trending themes or related fields concerning their field of interest but also helps them to identify new concepts and fields over time."

While topic modeling has recently gained traction in Library and Information Science (LIS), it has long been employed in computer science, digital humanities, biomedical engineering, and medicine. Its diverse applications include document classification, literature reviews, citation analysis, keyword extraction, recommendation systems, marketing analysis, and similarity searches.

A variety of sophisticated algorithms are available for implementing topic modeling. Among the most widely used are Latent Dirichlet Allocation (LDA), Structural Topic Modeling (STM), Dynamic Topic Modeling, Wikipedia-based Polyglot Dirichlet Allocation (WikiPDA), Latent Semantic Analysis (LSA), and BERTopic. Each algorithm offers unique strengths suited to different types of datasets and research objectives, making topic modeling a versatile and indispensable method in modern data analysis.

3.1 Review of Related Literature

Blei et al. (2003) laid the foundation of topic modeling and introduced the "Latent Dirichlet Allocation (LDA) model, an influential generative probabilistic framework for discrete data such as text corpora. They described LDA as a three-level hierarchical Bayesian model, where each document is treated as a mixture of topics and each topic as a distribution over words." This model became the cornerstone of subsequent developments in topic modeling and text mining.

Expanding on this, Wallach (2006) proposed a hierarchical model that integrates n-gram statistics with latent topic variables, thereby improving the interpretability of the inferred topics. Using the Gibbs EM algorithm on real datasets, Wallach demonstrated that this model outperformed unigram-based approaches and yielded more semantically meaningful results, particularly by reducing the dominance of function words.

Nallapati et al. (2008) extended topic modeling to include citation analysis through two novel models: Pairwise-Link-LDA and Link-PLSALDA. These models enabled joint modeling of text and citation networks, thereby enhancing the representation of scholarly communication, albeit with trade-offs in computational complexity.

In the same year, Titov and McDonald (2008) introduced a multi-grain topic modeling framework to extract ratable aspects from online reviews. Their method addressed the limitations of traditional models by distinguishing between global object properties and fine-grained aspects typically evaluated by users.

By bridging digital libraries and computational linguistics, Mehler and Waltinger (2009) used Dewey Decimal Classification (DDC) and metadata from the Open Archives Initiative (OAI) to create a classification model. Their work demonstrated the potential of topic models for automated thematic categorization in digital libraries.

Hu et al. (2014) identified the gap between machine learning-driven topic models and their practical usability by non-experts. They introduced Interactive Topic Modeling (ITM), a user-centric framework that encodes feedback into topic models, thus making them more adaptable and interpretable.

That same year, Roberts et al. (2014) introduced the Structural Topic Model (STM), which integrates document metadata into the modeling process. This semi-automated technique was especially useful for analyzing open-ended survey responses, estimating treatment effects, and understanding respondent behaviour.

Toraman and Can (2015) developed a priority-based algorithm for selecting news articles based on their importance and diversity using topic modeling. This was aimed at optimizing public news front pages in the absence of meta-attributes like click counts.

To address the multimodal nature of social data, Qian et al. (2016) proposed the Multi-modal Event Topic Model (mmETM) to capture both textual and visual elements from social media. Their framework effectively identified topic evolution and event summaries, outperforming several state-of-the-art techniques.

Nikolenko et al. (2017) tackled two key limitations in topic modeling: quality assessment and sub-topic detection. They proposed tf-idf coherence to improve topic evaluation accuracy. They introduced the Interval Semi-Supervised LDA (ISLDA) for focused sub-topic mining and validated their approach with a case study of ethnic discourse in Russian blogs.

Agrawal et al. (2018) exposed a critical flaw in LDA, order effects, whereby reshuffling input data leads to inconsistent topic outputs. This discovery raised concerns about reproducibility and accuracy in topic-based studies.

A methodological framework for the rigorous implementation of LDA in communication research was developed by Maier et al. (2018). Their study emphasized reliability and validity, demonstrating that LDA is a robust tool when combined with appropriate preprocessing and evaluation strategies.

Providing a panoramic overview, Kherwa and Bansal (2018) conducted a comprehensive survey of approximately 300 articles on topic modeling. They classified topic modeling techniques, posterior inference methods, LDA variants, and applications across domains such as bioinformatics, social networks, and scientific literature.

Hagen (2018) evaluated the utility of LDA for analyzing e-petitions, demonstrating that over 87% of the topics generated were interpretable by human judges. He highlighted the advantages of LDA over manual content analysis, such as bias reduction and the discovery of latent themes.

Hannigan et al. (2019) advocated for topic modeling in management scholarship, noting its capacity to uncover novelty, support inductive classification, and aid in understanding cultural dynamics. They positioned topic modeling as a bridge between algorithmic analysis and qualitative insight.

Vayansky and Kumar (2020) reviewed emerging topic modeling approaches that can handle short, sparse texts, temporal topic evolution, and topic correlations. They proposed a decision tree to help researchers choose suitable models based on dataset characteristics and analytical goals.

Dieng et al. (2020) introduced the Embedded Topic Model (ETM) to address the limitations of traditional models in handling large, skewed vocabularies. Using amortized variational inference, ETM delivered interpretable and high-performing results even with rare and high-frequency words.

Qiao and Williams (2021) applied LDA and sentiment analysis to explore Twitter discussions of global warming. Their study revealed dominant thematic clusters and a higher prevalence of positive sentiment in online discourse.

In a comparative study, Bellaouar et al. (2021) evaluated the performance of LDA and Latent Semantic Analysis (LSA) on NIPS conference papers. They analyzed the impact of text preprocessing techniques such as lemmatization and bigram collocation.

Ballester and Penner (2022) proposed new metrics to assess the robustness, descriptive power, and realism of topic models. They found that neural paragraph embedding methods could maintain stable and scalable document-topic representations beyond the capabilities of traditional models.

Qiang et al. (2022) systematically reviewed short-text topic modeling, categorizing approaches into three types: Dirichlet multinomial mixture-based, global co-occurrence-based, and self-aggregation-based. Their work also led to the development of STTM, the first open-source Java library for short-text topic modeling.

Ravenda et al. (2022) employed topic modeling to analyze municipal communication on Facebook, uncovering themes in social media posts from 502 Italian municipalities between 2016 and 2018.

In a systematic review, Natukunda and Muchene (2023) developed an LDA-based statistical model for automated title and abstract screening, thereby enhancing the speed and accuracy of evidence synthesis.

Finally, Mamasodikova and Ergasheva (2024) applied topic modeling to explore gender disparities in news coverage using an ever-expanding open news corpus. Their visualization-enabled methodology successfully tracked topic evolution and key real-world events over time using LDA topics generated monthly.

3.2 Application of Topic Modeling in Libraries

Topic modeling has increasingly proven valuable for organizing, analyzing, and enhancing access to information in libraries and digital collections. Its applications span from improving search and retrieval functions to identifying research trends and user needs.

(i) Enhancing Information Retrieval and Search Systems: Muresan and Harper (2004) demonstrated how topic modeling could generate "mediated queries" that more accurately represent users' information needs, enabling efficient search across large, diverse collections. Similarly, Haruechaiyasak and Damrongrat (2008) used LDA on Wikipedia articles to recommend highly relevant content based on topic similarity, even beyond hyperlink connections.

(ii) Improving Digital Library Services: Bethard et al. (2009) combined topic modeling with classification techniques to select resources for subject-based digital libraries. Newman et al. (2010) highlighted how topic models can automate subject tagging and improve content discovery in digital collections. Efron et al. (2011) addressed the challenge of metadata inconsistency in large collections and proposed methods for identifying low-information documents to refine topic modeling outputs.

(iii) Document Clustering and Recommendation Systems: Wang and Jie (2012) applied probabilistic topic modeling with Gibbs sampling for accurate clustering of digital books. Scherer et al. (2013) introduced a topic-based similarity function for efficient indexing in public library collections. Charlin et al. (2014) proposed the Collaborative Score Topic Model (CSTM), which combines user preferences and textual content for personalized document recommendations.

(iv) Subject Metadata and Multimedia Libraries: Choi et al. (2015) used LDA to analyze song interpretations, showing how topic modeling can enrich metadata in music libraries and potentially for literary collections. Cain (2016) emphasized how topic modeling can improve access to poorly indexed digital texts by identifying latent content structures.

(v) Domain-Specific Topic Exploration and Visualization: Mesbah et al. (2017) introduced "Facet Embedding," a domain-aware model for generating metadata and visualizing scientific trends. Abuhay et al. (2017) analyzed 16 years of conference papers to uncover topic evolution and interdisciplinary links through dynamic topic networks. Figuerola et al. (2017) applied LDA to the LISA database to identify core LIS research areas over nearly four decades.

(vi) Topic Trends and Knowledge Discovery in LIS: Kurata et al. (2018) used LDA to uncover hidden thematic structures within LIS literature. Al-Natsheh et al. (2018) addressed the issue of community-specific keywords and proposed a semantic tagging system that uses topic modeling to improve retrieval. Fang et al. (2018) combined topic modeling with regression analysis to identify trending and declining topics in LIS.

(vii) User Behavior and Service Optimization: Chen and Wang (2019) analyzed library chat transcripts using LDA and discovered that access to library resources was a dominant concern among users. Joo et al. (2020) analyzed Facebook posts from public libraries and found that posts about events and multimedia content had higher user engagement, and they classified content themes using topic modeling.

(viii) Evaluation, Research Trends, and Visualization: Papachristopoulos et al. (2019) integrated topic modeling with citation and altmetrics analysis to map the structure of digital library evaluation literature. Viet and Kravets (2019) scraped and analyzed arXiv papers to detect emerging academic trends. Timakum et al. (2020) applied text mining and topic modeling on top LIS journals to map evolving research areas. Meanwhile, Miyata et al. (2020) found a shift in the focus of LIS research toward digital and internet-based topics post-2015.

(ix) Language and Cross-Lingual Applications: Piccardi and West (2021) introduced the Wikipedia-based Polyglot Dirichlet Allocation (WikiPDA), enabling cross-lingual topic modeling for multilingual content classification.

(x) Classification and Indexing of Unstructured Texts: Mohammed and Al-Augby (2020) compared LDA and LSA for classifying 23 million words from unstructured scientific texts, concluding LDA offered superior coherence and clustering accuracy. Mazumder and Barui (2021) analyzed titles of LIS theses from Shodhganga using LDA to extract dominant research themes.

(xi) Recommendation Systems and Conference Analysis: Jelodar et al. (2021) applied topic modeling to eight computer science conference publications to build a recommendation system aligned with future research directions. Dantu et al. (2021) used topic modeling with co-citation analysis to explore research on healthcare applications of IoT, revealing five key thematic clusters.

(xii) LIS Theses and Doctoral Research Analysis: Kumar and Thakur (2022) employed topic modeling on Indian LIS doctoral theses to categorize them into ten major research domains, highlighting ICT as a key area.

(xiii) Topic Modeling for Visualizing and Comparing Research: Saha and Ghosh (2023) analyzed 734 LIS articles from Indian and international journals using topic modeling and visualization, identifying distinct research priorities between the two.

(xiv) Librarian Decision-Making and Reference Analysis: Koh and Fienup (2021) evaluated different topic modeling algorithms for chat reference data and found that probabilistic latent semantic analysis (LSA) outperformed LDA in interpretability and coherence.

(xv) Authorship, Verification, and Textual Analysis: Potha and Stamatatos (2019) explored topic modeling in authorship verification. They found that LDA was more effective when combined with profile-based and extrinsic verification methods.

(xvi) Indian Contextual Studies: Lamba and Madhusudhan (2019) examined nearly four decades of Indian LIS research, identifying bibliometrics, ICT, and user studies as dominant themes.

4. DATA VISUALIZATION (DV)

Data visualization (DV) refers to transforming abstract, non-coordinate data into meaningful graphical or pictorial formats. It allows users to interpret complex datasets more efficiently than traditional text-based methods. As Lamba and Madhusudhan (2022) note, "Visualization is a method of externalizing information, making it visible, interactive, and easier to manipulate through visual systems." This aligns with the well-known adage, "A picture is worth a thousand words," which emphasizes that visuals communicate data-driven narratives more effectively than dense text (Finch & Flenner, 2016).

Zakaria (2021) highlights that graphical representations are cognitively more persuasive than numerical tables, enabling faster comprehension of relationships among data. Embarak (2018) further explains that DV simplifies massive datasets into digestible visuals, aiding clearer communication and insight generation. Similarly, Pant and Rajput (n.d.) stress that DV is a powerful means of describing large-scale data in accessible and engaging ways.

Sadiku et al. (2016) recognize DV as a universally adaptable tool with speed, simplicity, and cross-disciplinary applicability. According to Lamba and Madhusudhan (2022), DV also supports problem-solving, data interpretation, and insight-sharing capabilities, enhanced through interactive and computational tools.

4.1 Data Visualization in Libraries

In library and information science, data visualization is rapidly emerging as an essential practice for managing and interpreting complex information resources. Siddiqui (2021) emphasizes that DV provides intuitive visual formats, charts, graphs, and maps that reveal trends and patterns across large datasets, making data more accessible to library users.

Midway (2020), however, reminds us that the art of data visualization must go hand in hand with accuracy. Misrepresentations, even if unintentional, can mislead users and obscure insights. Hence, thoughtful design and precision are vital.

Murphy (2015) notes that the growing complexity of digital content and aggregated data has made DV a necessary tool in academic libraries. It is now employed for collection analysis, usage tracking, expenditure visualization, and overall service enhancement. Finch and Flenner (2016) add that DV can support decision-making by illuminating citation patterns, suggesting titles for weeding, mapping scholarly communication, and analyzing subject relationships.

As Aavarti and Kumbar (2022) state, DV tools offer academic libraries new opportunities to contribute to research by integrating visualization into regular services. These tools can enhance library value by presenting data in ways that engage faculty, researchers, and students alike. Eaton (2017) further asserts that academic libraries are well-positioned to leverage ICT and DV technologies to deliver impactful research support.

Murphy (2013) points out that DV strengthens the library’s role in research support, enabling librarians to organize, interpret, and present data meaningfully. Aavarti and Kumbar (2022) also recognize that while academic libraries are still developing their capabilities in this domain, DV holds immense potential in visualizing research outputs, enabling deeper analytics, and supporting user needs through charts, infographics, networks, and more.

According to Aghassibake et al. (2020), offering DV instruction also presents an opportunity to address broader pedagogical goals, particularly those related to emerging digital tools and evolving librarian roles. Mahajan and Gokhale (2020) classify the advantages of DV into two broad areas: (i) visual impact, making data memorable and compelling, and (ii) functionality, improving data navigation, decision-making, and service planning.

Murphy (2013) and Brigham (2016) emphasize that DV empowers librarians to creatively and strategically manage and present complex data from varied sources. It assists with strategic planning, reveals user behaviour, supports evidence-based decisions, and visualizes institutional priorities.

Eaton (2017) adds that DV enables librarians to gain deeper insights from data, thereby enhancing their contributions to research and institutional goals. Zakaria (2021) further notes that DV demonstrates the library's value and effectively markets librarians' expertise. Aavarti and Kumbar (2022) affirm that globally, academic libraries have embraced DV support services, offering consultancy, workshops, training, and dedicated DV spaces to foster research and innovation.

5. FINDINGS OF THE STUDY

The key findings from the analysis of the publications are presented below, supplemented with tables and graphical visualizations to highlight trends and patterns.

(i) **Publication Timeline (2003–2024):** A total of **73 scholarly works** spanning two decades were analyzed. Notably, **75% of the publications were published within the last ten years**, reflecting a sharp increase in interest and application of topic modeling and data visualization in recent years. The majority of these contributions were concentrated between **2018 and 2022**, indicating the subject area's current and growing relevance. *(Figure 2).*

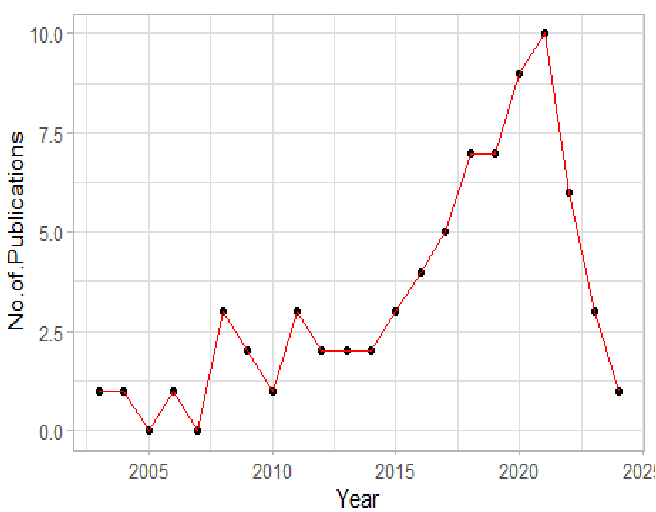

Figure 2: Year-wise distribution of publications

(ii) **Document Types:** The review encompassed four major categories of publications: **journal articles, conference proceedings, book chapters, and theses**.

- **Research articles** accounted for the largest share (**70%**), underscoring the prominence of peer-reviewed scholarly communication in this field.
- **Conference papers** accounted for **18%**, followed by **book chapters (9%)** and **doctoral theses (3%)**, indicating a growing academic interest across diverse platforms *(Table 1).*

Table 1: Types of publications

Types of publications	No. of Publications
Journal Articles	51
Book chapters	7
Conference Papers	13
Theses	2

(iii) **Authorship Patterns:** The documents analyzed exhibited a range of authorship patterns, from single-author contributions to large collaborative works.

- Publications with **two authors** were the most common (**35%,** or 26 papers).
- **Single-author** and **three-author** publications accounted for **18%** each (13 papers each).
- Fewer documents were found to have **7, 8, and even 11 authors,** reflecting interdisciplinary and collaborative research practices in some cases. *(Figure 3).*

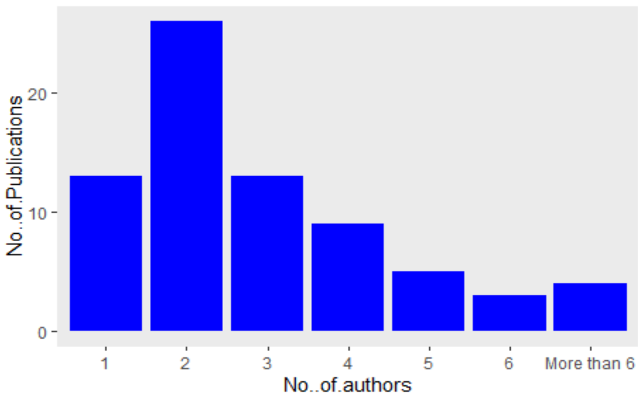

Figure 3: Authorship Pattern of Publications

These findings reflect the dynamic and interdisciplinary nature of topic modeling and data visualization research in the library science context, with a clear trend towards a collaborative, data-intensive scholarship in recent years.

6. CONCLUSION

Topic modeling is an emerging and versatile technique that, when applied effectively, can benefit librarians and other information professionals. This study explores the theoretical and practical aspects of topic modeling in the Library and Information Science (LIS) field, including various algorithms for analyzing datasets. It examines the advantages, limitations, uses, challenges, and real-world applications of topic modeling. It helps the libraries in various day-to-day applications ranging from creation of document clustering and recommendation systems, subject metadata and multimedia libraries, to discovering trending topics and knowledge in LIS, studying the user behaviour and service optimization, for cross-lingual applications, classification and indexing of unstructured texts, and can be used for analysis of LIS theses, doctoral research, conferences, etc. Additionally, the study highlights the importance of data visualization for presenting complex, large datasets in clear, accurate, and efficient graphical formats. Visual representations are particularly impactful, as people tend to retain and prioritize visual information over raw data. As such, data visualization is widely valued across academic disciplines. This study aims to support librarians, data analysts, and researchers in understanding and applying topic modeling and visualization techniques to enhance library services, contribute to scholarly communication, and foster their professional growth.

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