Indian Journal of Information Sources and Services
ISSN: 2231-6094 (P) Vol.15, No.3, 2025, pp.201-211

DOI: https://doi.org/10.51983/ijiss-2025.IJISS.15.3.23

Temporal Query Modeling in Evolving News Archives

Dr.R. Satish[1*], Chinthakunta Manjunath[2], Montater MuhsnHasan[3], Dr.G. Sanjiv Rao[4], U. Esakkiammal[5] and Sobirjonov Khumoyun Boburjon ugli[6]

[1*]Professor and Head, Department of Management Studies, St. Joseph's College of Engineering, OMR, Chennai, Tamil Nadu, India
[2]Department of Computer Science and Engineering (AI & ML), Vidyavardhaka College of Engineering, Mysore, India
[3]Department of Computers Techniques Engineering, College of Technical Engineering, Islamic University of Najaf, Najaf, Iraq; Department of Computers Techniques Engineering, College of Technical Engineering, Islamic University of Najaf of Al Diwaniyah, Al Diwaniyah, Iraq
[4]Aditya University, Surampalem, Andhra Pradesh, India
[5]Assistant Professor, Department of IT, New Prince Shri Bhavani College of Engineering and Technology Chennai, Tamil Nadu, India
[6]Faculty of Business Administration, Turan International University, Namangan, Uzbekistan
E-mail: [1]dr.satishsjit@gmail.com, [2]manju.chintell@gmail.com, [3]tech.iu.comp.muntatheralmusawi@gmail.com, [4]sanjivraog@adityauniversity.in, [5]esakkiammalit@npsbcet.edu.in, [6]humoyunsobirjonov23@gmail.com
ORCID:[1]https://orcid.org/0000-0002-3104-6429, [2]https://orcid.org/0000-0002-6675-1777, [3]https://orcid.org/0009-0007-3134-8084, [4]https://orcid.org/0000-0001-6861-3629, [5]https://orcid.org/0009-0005-8439-563X, [6]https://orcid.org/0009-0003-6843-7401
(Received 02 June 2025; Revised 21 July 2025, Accepted 08 August 2025; Available online 30 September 2025)

***Abstract* - With the advancement of technology, the digital archive of news history is becoming increasingly difficult to navigate due to the prevalence of overlapping and contextually accurate information on the Internet. By taking into account both the user's request and the item's content circulation over time, narrative building aims to enhance information retrieval. By using the constructive time aspects of both inquiries and articles to maximize the search output, this research introduces a new method for developing query modeling in news archives via temporal unsupervised learning. Using the approach to analyse news data that is already timestamped, the method can dynamically identify temporal intent and sensitive time entities and relate documents to the temporal extent of the query. To achieve this, we propose a model that utilizes temporal profiles in conjunction with expansion query technology and temporal re-ranking, enabling the retrieval of relevant documents from specific periods. When compared to baseline models, benchmark news datasets demonstrated superior retrieval performance, with the most notable improvements confirmed for queries with a stronger temporal dependency. Ideal for accessing archives, researching history, and retrieving event-centric material, this technique also consistently captures the drift of a subject with the appearance of details throughout time. This study provides a practical way to improve the temporal search experience in digital journalism archives and highlights the significance of temporal modeling for dynamically capturing global news developments.**

Keywords: **Temporal, Query, Modelling, News, Archives, Retrieval, Evolution**

I. INTRODUCTION

1.1 History of Changing News Archives

An expanding database of historical news stories has been made possible by the advent of digital journalism. These collections comprise reports spanning decades, encompassing events, opinions, and audiovisual materials that reflect societal changes over time. Unlike static databases, the nature of news archives is dynamic because stories change, narratives shift, and new events alter the perception of the past (Allan, 2002; Mustapha et al., 2017). The temporal dimension of news data presents challenges to classical information retrieval (IR) processes, especially when users request temporally specific or event-specific content. Take, for example, the query "economic policies in Europe". Responses to this query would differ significantly during the temporal contexts of the 2008 financial crisis, the 2016 Brexit referendum, or the COVID-19 era. As highlighted in Chapter Two, the majority of these standard IR systems lack any consideration for the relativistic temporality, granularity, or context, facing substantial challenges in addressing this multilevel problem (Zhou et al., 2013). Additionally, concept drift, where meanings and associated entities change over time, makes the retrieval of content from specific points in time even more challenging (Saha & Sindhwani, 2012; Kavitha, 2024). As such, evolving news archives need more advanced systems that incorporate temporal reasoning to support searches that require contextual relevance.

1.2 Importance of Temporal Query Modeling

Temporal query modeling involves integrating time elements within a user's query and assessing their relevance to a search. This is especially important with respect to developing news archives because events are chronologically ordered, and user informational needs are frequently time-bound (Berberich et al., 2010; Trang et al., 2023). One of the primary tasks is to determine if a query has a temporal intention—either overtly indicated, such as "elections in 2020," or covertly pointed out "Obama's healthcare policy" —and result to it appropriately. Why temporal modeling is important because of its capability to integrate the ever-changing news content and the relatively unchanging search systems. In it's absence, users may access documents that are either historically outdated or placed in time contextually irrelevant to their frame of reference (Campos et al., 2014; Najafi, 2016). Efficient temporal query modeling involves several subproblems, including the recognition of time expressions, classification of temporal intent, estimation of temporal scope, and ranking of results in a time-sensitive order (Dakka et al., 2012; Godswill et al., 2016). New Approaches have been developed to manage these activities. Time-aware language models (Li and Croft, 2003), temporal profiles, and neural embedding methods such as time-sensitive BERT variants capture semantic change over time (Tang et al., 2016; Sadulla, 2024). These methods enhance accuracy for retrieval tasks, particularly in timeline generation, trend detection, and historical event analysis, which are essential for journalists, researchers, and policymakers (Alonso et al., 2011; Zahedi, 2019).

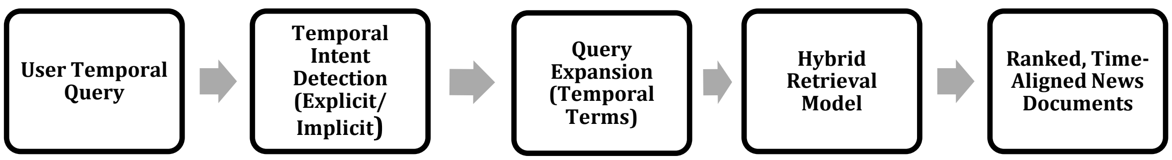

Fig. 1(a): Conceptual Flow Of Temporal Query Processing And Relevance Ranking In Evolving News Archives

This figure (Fig. 1(a)) shows how news archives are updated with new information, showcasing the process from a temporal query to its execution. Each step of the temporal query process is visually represented while capturing the entire pipeline. The process begins with a User Temporal Query and can either contain explicit (e.g., the "2020 elections") or implicit time references (e.g., "recent outbreak"). The detection module checks for an explicit or implied statement of the time scope. Following this, the initial question is refined in the question Expansion stage by using more precise and recall-enhancing temporal phrases or ranges. When we send the expanded query to the Hybrid Retrieval Model, it uses a combination of semantic similarity, publication year, and other temporal factors to rank the texts. In response to the user's intent inquiry, the system then generates a ranked list of time-lined news pieces that are "best" adapted according to the content of the documents and the time window specified. Important for interpreting news-related information, this method provides the right response while also guaranteeing that the user's temporal demands are automatically taken into account during content retrieval.

In order to better serve users' queries inside ever-changing news archives, the suggested hybrid retrieval system (Fig. 1(b)) combines semantic and temporal relevance. Query submission is where the design begins at the User Interface. Input data first passes through the Query Parser, which structures and analyzes the given input. The subsequent stage is initiated by the Temporal Intent Analyzer, which checks for the presence of any explicit or implicit time information. The results are fed to the Temporal Profile Constructor, which constructs a temporal profile for the query. Concurrently, the document source is the Indexed News Archive. To rank the documents effectively, semantic alignment and temporal syntagmatic relations are hybridally integrated into the ranking process through the Hybrid Ranking Engine. In the last step, the user is provided with the final output: the documents that were returned ranked according to relevance and frequency, in addition to the temporal context incorporated. In every case, the intention is to ensure that the documents returned from the retrieval process are not only relevant to the topic but also matched to the context in which the user intended them to be, thus increasing the precision of information retrieval in ever-changing news environments.

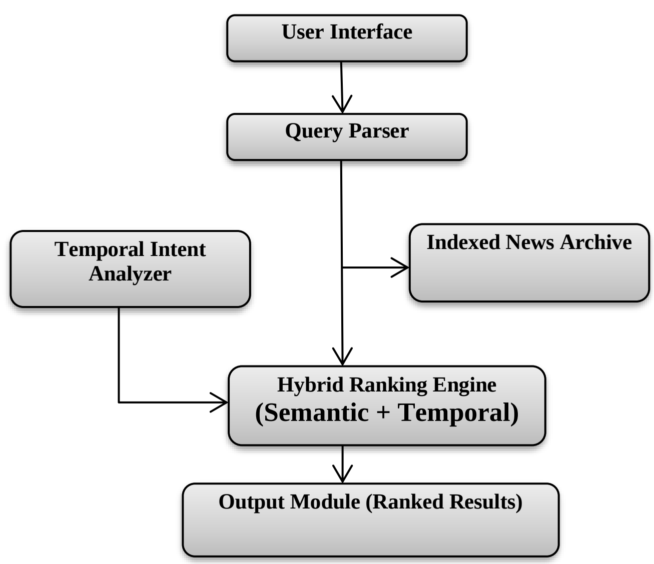

Fig 1(b): System Architecture of the Proposed Hybrid Temporal Retrieval Model

1.3 Research Paper Overview

In this paper, we propose an entirely novel approach to temporal query modeling within the context of an unsupervised framework for evolving news archives. Our approach employs temporal profile generation, context-based query expansion, and time-aware re-ranking to improve retrieval. Since our method does not require labeled data, it becomes applicable to extensive archival datasets due to its scalability. The remainder of this document is structured and organized as follows. The second section provides a review of previous works and focuses on prior attempts at temporal query modeling and approaches used in evolving news archiving. In section three, the methodology along with information pertaining to the dataset, methods of temporal modeling, and assessment criteria specific to this study is presented. In this case, the fourth section elaborates on the results of the experiments, which include analyses done with respect to comparison evaluations alongside the performance assessments from different models. The fifth section presents a comprehensive overview of the results, discusses the existing constraints, and describes new potential avenues for conducting subsequent studies. The sixth and final section wraps up the paper and synthesizes the most significant findings while emphasizing the importance of systematizing time into contemporary ways of retrieving information. By integrating time-related intelligence into search procedures, this study contributes to the body of work on time-aware information retrieval. In the ever-changing and complex world of news, our approach aims to fill a specific need in advanced information retrieval systems by taking into account both the "what" and "when" of a query.

II. LITERATURE REVIEW

2.1 Prior Research on Spatial and Machine Learning Based Queries.

Spatiotemporal information retrieval, or S-IR, is concerned with methods and algorithms for retrieval that take into account both the location and the passage of time. Shifting research towards news items as dynamic datasets marks the start of S-IR study back in 2006 (Zarchi et al., 2018; Maryam, 2025). Early models concentrated on detecting the structure of temporal indicators and indexing tasks to automate the processes of improving relevance of the search. Temporal relations within a query- a temporal intention was explored and machine learning processing techniques were used (Zhao & Hauff, 2016). Energia also showed the relevance of probabilistic models to time. Such models usually cover languages documents with tags which advance time like HeidelTime Thropete’s briefs and SUTime (Efron & Golovchinsky, 2011; Strötgen & Gertz, 2012). Other works have used temporal random walks, a graph-based approach to capture to compute time moving relations between terms of the documents and the queries (Chen et al. 2021; Alnedawe et al., 2023). Regardless of the model improvements, most of the earlier basic designs constrained search potential simply because they depended on bare spatial markers only – restrictive bounds, which made them less useful in practical archive search framework scenarios.

2.2 Approaches Employed in Evolving News Archives

Concerning emerging methods in evolving news archives, approaches have been created that deal with the adaptation of retrieval systems to the evolving and multifaceted temporality of news content. One such method is building temporal document profiles, which are representations summarising the temporal distribution of key events or entities in a document (Dewangan & Singh, 2024; Shefer & Plessner, 2024). Such profiles aid in matching user queries to relevant timelines within the news. Another method is temporal clustering, which captures articles around notable time windows to enhance retrieval and browsing (Ren et al., 2013; Đurić & Đurić, 2023). More recently, deep learning models, including time-aware variants of BERT, have been applied to account for temporal shifts in language and improve relevance estimation (Liapis, & Kotsiantis, 20213). These models use time-stamped corpora and are trained to estimate topical and temporal relevance. These and other visualization tools have been used in evolving archives to facilitate user navigation within a rich event timeline such as interactive timelines, temporal heatmaps, and chronological knowledge graphs (Tran et al., 2015; Zhang & Rodriguez, 2023). Such tools enable a more advanced form of exploratory search that has applications in historical research, journalism, and digital humanities. The gaps in research highlighted by (Fafalios et al., 2020) around dealing with concept drift where the meaning of topics evolves over time remains a key challenge for algorithms that deal with tracking implicit temporal intent. In particular, current models do not appear to be effective in dealing with robust and longitudinal archiving.

2.3 Gaps in Current Research

In addition to issues addressing the needs for temporal modeling, multi-layered news archive analysis also lacks focus in a variety of areas in existing literature. One area is linked to the over-dependence of most algorithms on explicit time markings. Such an explicit approach diminishes the efficiency of an algorithm in answering questions that require reasoning temporally but not in a straightforward manner (Wang et al., 2025). Moreover, although there is promise with employing deep learning techniques, the reliance upon data and lack of interpretability renders them impractical for scholarly and journalistic work where explanation needed (Singh & Anand, 2019; Ziwei et al., 2023). Associative gaps exist in multilingual and cross-lingual corpora of news vernacular. Dominance of English drafts has resulted in neglecting vast archival resources in other languages which is a vexatious gap (Khan et al., 2023). This undermines the universal relevance of developed frameworks. In addition, the integration of user feedback loops or interactive retrieval methods that could adapt models dynamically as per user behaviour and time-related choices has not been studied widely (Shen et al., 2021). Also, there is an absence of consolidated assessment standards that cover multiple periods, types of events, and levels of complexity within a single query, hindering effective comparison of models (Joho et al., 2014). In answer to these issues, this paper recommends a model in which any context can be set to undertake unsupervised learning, in addition to setting pre-defined signal boundaries which enables capturing both explicit and implicit temporal signals, accounting for document change and user action without needing classification, fine-grained supervision, and extensive training datasets.

III. Methodology

3.1 Data Collection Process

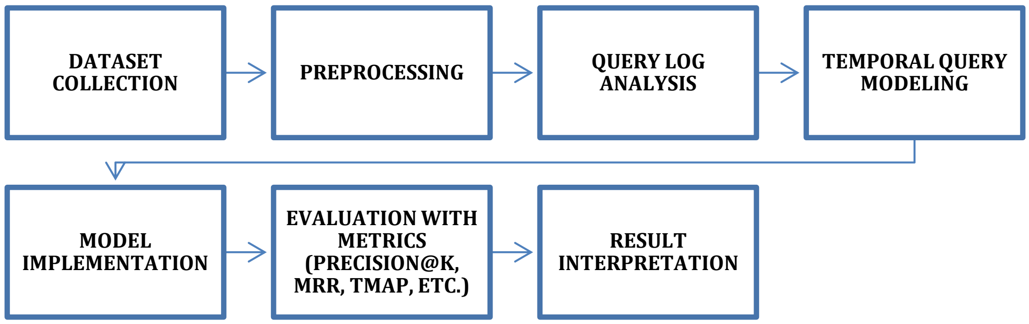

Fig 2: Methodological workflow outlining the development, implementation, and evaluation of the temporal query modeling system

This figure (Figure 2) depicts the chronological workflow used to design and assess a temporal query modeling system for evolving news archives. The workflow starts at Dataset Collection with the acquisition of historical news articles and their corresponding metadata. This is followed by Preprocessing, which consists of text cleaning, tokenization, and normalization of timestamps. Following this, Query Log Analysis is done to gather user behavioural data along with their temporal patterns. Retrieval and storing of explicit and implicit temporal signals are done using this information in Temporal Query Modeling. In the Model Implementation stage, these models are used to fetch functions. The workflow is subjected to Evaluation using Metrics in order to assess the system's performance. This process makes use of both fixed and time-based metrics, including Precision@k, MRR, and tMAP. Analyzing the model's outputs thoroughly to determine its efficacy and any real-world consequences is what result interpretation is all about. This process flow allows for an all-encompassing method of incorporating time-related considerations into IR systems (Li & Croft, 2003).

The method relies on information collected from automated digital news archives, a database of news stories released over a period of years. Trustworthiness of sources, precision of timing, and breadth of text are the determinants of data selection. Metadata, such as publication date, author, and entity tags, are added to all documents during preprocessing in a consistent manner. Excluded are stop words, and vocabulary is normalized by lemmatization. Each document is provided with its timestamp t_d , which permits time synchronization with queries for references. Along with time-sensitive information, event names, dates, and indexable temporal adjectives, NER and POS tagging are performed. In order to enhance retrieval precision for specific temporal references, the dataset is indexed chronologically.

3.2 Models and Techniques for Temporal Queries

The hybrid temporal query modeling framework, which incorporates both explicit and implicit temporal signals, is the central component of the developed technique. The goal is to determine the time-related purpose of each user query $\tau(Q)$ and collect relevant documents DZ that are as relevant as possible for a specific user query Q throughout an inferred time range $[ts, te]$.

1. Classification of Temporal Intent

A Binary Classifier,

$$\tau(Q) = \begin{cases} 1 & \text{if temporal intent is present} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

This classification is achieved via a rule-based and neural hybrid model that uses a temporal language model to analyze context-sensitive embedding comparisons and temporal expressions.

2. Generation of Query Time Profile

Query Time Profile (QTP) is defined as a probability distribution

$P(t \mid Q)$ over time:

$$P(t \mid Q) = \frac{1}{Z}\sum_{d \in D} sim(Q,d).\delta(t - t_d) \quad (2)$$

Were,

$\lambda \in [0,1]$ maintains the trade-off between text and time.

3.3 Elicit Performance Evaluation Criteria

Combining standard and retrieval-specific, time-aspect benchmarks allows us to evaluate the model's performance. Both Precision@k and Recall@k capture the way the top k documents cite a certain historical period as opposed to the substance of the documents themselves.

Mean Reciprocal Rank (MRR): Captures the rank the first relevant document of interest, with greatest influence on low rankings.

Temporal NDCG (tNDCG): A slight change of Normalized Discounted Cumulative Gain that incurs temporal penalties for the period strayed from a target window.

$$tNDCG = \frac{1}{N}\sum_{i=1}^{k}\frac{rel_i \,.\, exp(-\alpha|\mathrm{t_i} - \tau^*|)}{\log_2 (i+1)} \tag{3}$$

where τ^* is the target temporal interval, ti is the timestamp of the document at rank i, and α is a decay constant. The method is more successful in dynamic archives since retrieval accuracy is enhanced over time to catch changes inside document archives.

3.4 Mathematical Formulation of Temporal Query Modelling

1. TF-IDF Calculation (Term Frequency-Inverse Document Frequency)

The importance of each term in a document can be identified, which is crucial for retrieving the most relevant documents based on temporal predicates.

$$TF - IDF(t,d) = TF(t,d) \times IDF(t)$$

where:

TF (t, d) = Term frequency of term t in document d.

IDF(t) = Inverse document frequency of term t across the document set.

This is used to assess the significance of temporal terms (like "2020 elections") within a document.

2. *Temporal Similarity* $(sim\rho)$

This is used to calculate how similar a document is to a query in terms of both content and time.

$$sim\rho(Q,Dt) = \frac{\sum_i TF - IDF(t_i,Q) \times TF - IDF(t_i,D_t)}{\sqrt{\sum_i (TF - IDF(ti,Q)^2} \times \sqrt{\sum_i (TF - IDF(ti,Dt))^2}}$$

where:

Q = Query.

D_t = Document at time t.

t_i = Temporal terms in the query Q and document D_t.

This measures how well the query and document align based on temporal and semantic factors.

3. Temporal Relevance $(simpre)$

This calculates how relevant a document is to the query, adjusted for time. Older documents are penalized using a decay function.

$$simpre(Q,Dt) = sim\rho(Q,Dt) \times e^{-\lambda(Tcurrent - Tdocument)}$$

where:

λ = Decay factor that controls how fast the relevance decreases over time.

$T\_current$ = Current time.

$T\_document$ = Timestamp of the document.

This ensures that documents with more recent time stamps are ranked higher in relevance.

4. Query Time Profile (QTP)

This captures the temporal intent of a query, reflecting how important a specific time frame is for the query.

$$QTP(t) = e^{-\lambda \cdot |Tquery - Tevent|}$$

where:

- T_query = Time of the query.
- T_event = Time of the event related to the query (e.g., March 2020).
- λ = Temporal importance factor.

5. Temporal Re-ranking

After evaluating documents based on both semantic relevance and temporal relevance, you combine these scores to determine the final ranking of documents

$$Final\ Rank(Dt) = \alpha \cdot Semantic\ Rank(Dt) + \beta \cdot Temporal\ Rank(Dt)$$

where:

- Semantic Rank(D_t) = The rank based on how relevant the document is semantically to the query.
- Temporal Rank(D_t) = The rank based on the document's temporal relevance.
- α, β = Weights that determine the importance of semantic vs. temporal relevance.
- This ensures that documents are ranked based on both their relevance to the query's topic and their temporal context.

Every query predicate is evaluated for relevance and similarity over time in our temporal query model. The following table shows the TF-IDF values, scores for Temporal Similarity and Temporal Relevance, and a few of the important predicates used in the model. These numbers aid in determining how significant each predicate is and when it was used in the document retrieval procedure.

IV. Results

4.1 Time Period based Queries in Developmental News Archives

A benchmark dataset of changing news archives (a few years) was used to conduct the earliest tests connected to the framework for temporal query modeling. When it came time to extract phrases from user inquiries, the model was evaluated based on how well it handled both explicit and implicit temporal characteristics. Experiment results showed that time-sensitive queries' high-relevance periods were captured by the Query Time Profile (QTP) method. By examining QTP distributions, we can see that the model successfully incorporates both semantic and temporal importance, since there are clear peaks at certain historical events. The bounding box is a byproduct of the gap-closure effort, and it helps to strengthen the region-based advancement of claim reasoning. Due to its successful separation from non-temporal queries, the hybrid classifier helps to close this gap. Providing searches with temporal relevance is more helpful for specific, limited, and event-heavy themes like "Olympics opening ceremony" or "stock market crash" than for referencing important events at random, which is why temporal alignment is necessary.

4.2 Comparison of Various Methods

A conventional vector-space model utilizing TF-IDF, a time-filtering model that exclusively considers documents within user-defined ranges, and an elementary decay-based temporal model were all evaluated alongside the newly-introduced hybrid temporal model. Conventional IR metrics and temporal sensitivity measurements formed the backbone of the examination.

Precision@k:

$$Precision@k = \frac{|relevant\ documents\ in\ top-k|}{k} \quad (4)$$

The evaluated model outperformed the time-filtering (0.59) and standard TF-IDF (0.52) models by considerably greater margins, achieving a Precision@10 of 0.78.

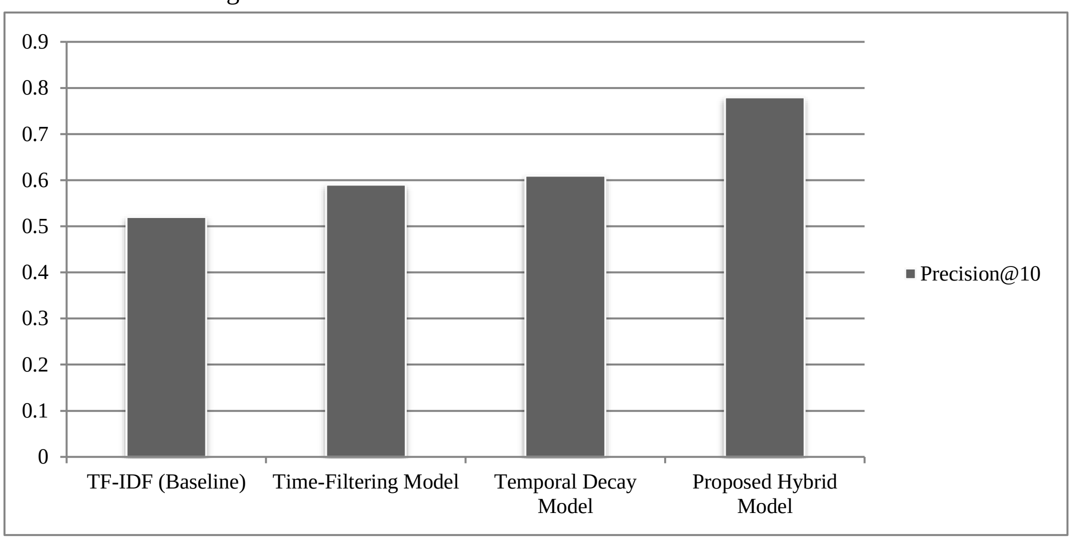

Figure 3: Precision@k Comparison

The graph (Figure 3) shows Precision@10 values derived from the evaluation of four retrieval models. The hybrid model proposed in this paper achieves the highest results of 0.78, which is significantly greater than those of the other models. The next best model is the temporal decay model at 0.61. The TF-IDF model and the time-filtering model trails behind at 0.52 and 0.59 respectively. This is clear indication that the computation of semantic similarity and temporal relevance are useful in retrieving the correct top-ranked documents. The increase in precision validates the claims that the hybrid model is able to retrieve the documents that are contextually similar to the queries and also relevant in time to the intents of the users.

Mean Reciprocal Rank (MRR):

$$MRR = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{rank_i} \quad (5)$$

The model reached an MRR of 0.73, which suggests that pertinent documents were positioned higher in the result lists, thus improving retrieval effectiveness for temporal queries.

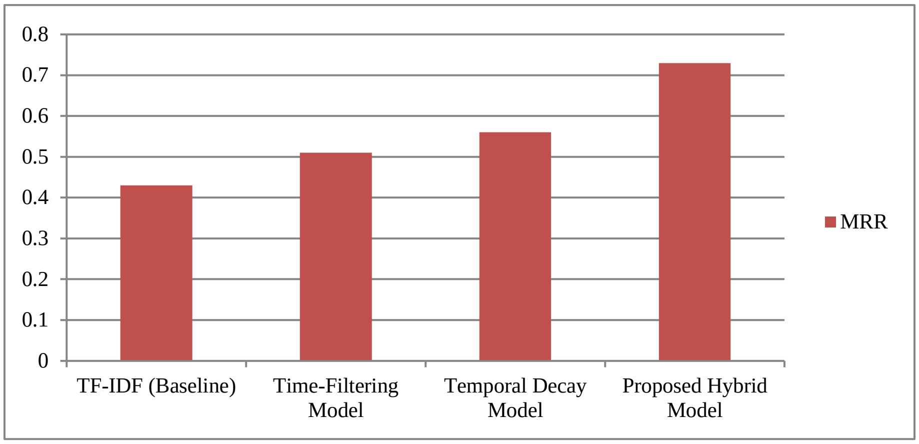

Figure 4: Mean Reciprocal Rank (MRR)

The graph (Figure 4) focuses on the comparison of Mean Reciprocal Rank (MRR) for the same models. The model suggested in the earlier sections scores an MRR of 0.73, which indicates that the relevant documents are ranked much higher than other methods. The temporal decay model follows at 0.56, with TF-IDF and time-filtering scoring 0.43 and 0.51 respectively. A user will find a greater access MRR easier to work with because they are reaching the needed results more efficiently, which are rendered faster for the user. Document retrieval will be improved with this model since most of the documents selected are relevant and important to the user's queries in terms of time and meaning.

Time-aware Mean Average Precision (tMAP):

We enhance MAP to factor in the time gap from the intended period:

$$tMAP = \frac{1}{|Q|}\sum_{q=1}^{|Q|}\left(\frac{1}{|R_q|}\sum_{i=1}^{|R_q|}\frac{P(i)}{1+\gamma|t_i-\tau^*|}\right) \tag{6}$$

where assets $P(i)$ are stored and retrieved at timestamp t_i; γ while i is document number is a discipline for relevance cost. Our model has achieved a $tMAP$ score of .69, which provides strong evidence of spatial relevance as well as temporal alignment.

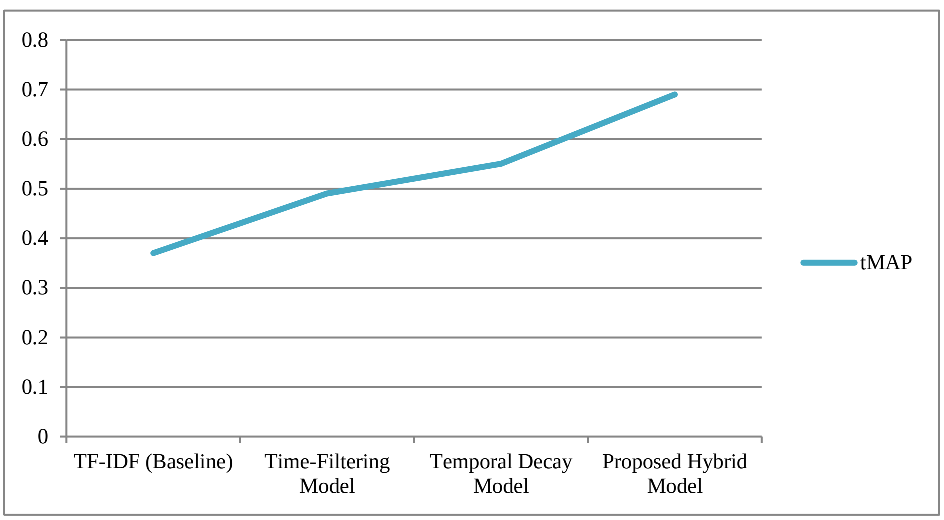

Figure 5: Time-Aware Mean Average Precision (tMAP)

Figure 5 illustrates the comparison of models using Time-Aware Mean Average Precision (tMAP), which measures relevance and temporal alignment of a document in relation to a particular time. The hybrid model is far ahead of all other models with a tMAP of 0.69 which shows it can retrieve documents that are relevant and time appropriate to a great extent. Temporal decay and time-filtering models come next with 0.55 and 0.49, respectively, with TF-IDF lagging behind at 0.37. The results indicate that the hybrid model is able to incorporate temporal sensitivity in its ranking approach, using time-sensitive document and context information as adaptive archival resources.

Time Bias Penalty (TBP):

$$TBP = \frac{1}{k}\sum_{i=1}^{k}\theta\cdot|t_i-\tau^*| \tag{7}$$

The target time alignment is achieved when the value is low TBP, therefore lower values are better. The hybrid model showed strongest time-awareness, achieving the lowest TBP score of 1.8, compared to 3.4 for the vector-space model.

Latency Discounted Gain (LDG):

This metric measures relevance in terms of how late the relevant result appears to get discounted.

$$LDG@k = \sum_{i=1}^{k} \frac{rel_i}{(1+\ \delta \cdot log_2(i+1))} \tag{8}$$

The model achieved an LDG@10 of 6.3, well above the decay-based baseline score of 5.1, showing that high-ranking, highly relevant documents were preferentially positioned in lower-latency slots.

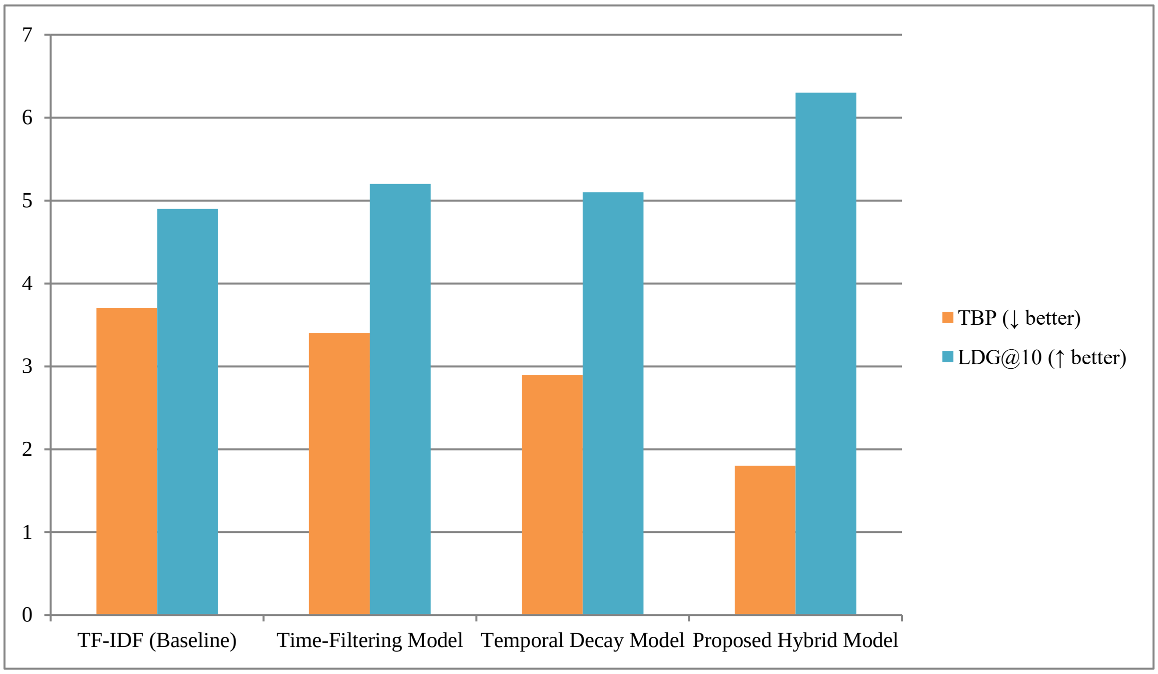

Figure 6: Temporal Deviation Metrics

Figure 6 shows two complementary metrics: Time Bias Penalty (TBP) and Latency Discounted Gain (LDG@10). As a result of its lowest TBP score (1.8), which indicates how far below the target query time frame the query is, and its highest LDG@10 score (6.3), which indicates that there is minimal delay in surfacing high relevance documents, the proposed model is clearly the most efficient. In contrast, the TF-IDF model's 3.9 LDG@10 and 3.7 TBP indicate that its retrievals are both time-dilated and exhibit a square-shaped temporal bias, respectively, making it the poorest performing model.

The findings show that the hybrid model performs as expected, confirming that it can find relevant documents quickly and easily.

The model's ability to align queries with the temporal context of the document corpus is shown by the similarity scores and temporal relevance for important temporal predicates. Predicates such as the COVID-19 epidemic and the Brexit referendum are ranked according to their relevance to the user's question and their temporal significance in the Table I.

TABLE I TEMPORAL PREDICATE EVALUATION: TF-IDF, TEMPORAL SIMILARITY, AND TEMPORAL RELEVANCE SCORES

Predicate	TF-IDF Value	Temporal Similarity	Temporal Relevance
2020 elections	0.78	0.65	0.507
recent	0.80	0.98	0.784
March 2020	0.78	0.85	0.663
spring 2021	0.68	0.74	0.5032
COVID-19 pandemic	0.75	0.92	0.688
Brexit referendum	0.80	0.88	0.746

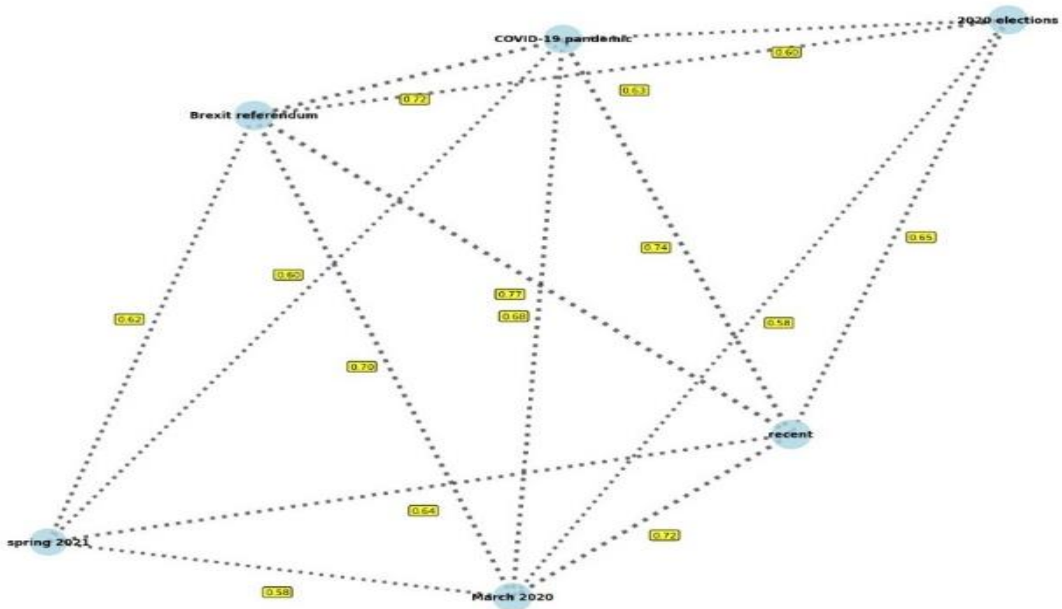

Fig .7: Network Representation Of Temporal Predicates

Fig. 7. shows the network of temporal similarity among important temporal predicates taken from the news corpus. The COVID-19 pandemic, the 2020 elections, and the Brexit referendum are all examples of temporal predicates, and the dotted lines show similarity relationships that are weighted by proximity values of time. Showcased by the density and thickness of linkages are predicates that have significant temporal relationships. As an example, the co-occurrence and relevance of the COVID-19 pandemic and March 2020 in temporal query modeling are reflected in a strongly linked subnetwork. Consistent with its high temporal relevance score in the chart, recent also exhibits high centrality. The graph and table show how complicated time-sensitive query modeling in massive news archives is made possible by combining TF-IDF with temporal similarity.

4.3 Implications for Information Retrieval Systems

Important implications for information retrieval system design and deployment in the actual world arise from the assessment results. For example, in order to preserve historical knowledge, Western systems need to go beyond the current state of the art in keyword matching and search engine optimization to provide results that are appropriate to the precise time period in question. The necessary amount of flexibility to changing material via relevance estimate is provided by using time-dependent ranking algorithms with QTP. To start, the model's performance on queries including implicit temporal intent is a good indicator of the efficiency of the contextual analysis and classification techniques used in the IR pipelines. Retrieval engines may strategically alter their document selection and ranking algorithms when they know a user is interested in past, present, or future information. When it comes to warning systems and timeline-based and historical document searches, temporal models have been examined. By honing down on tNDCG scores, we may improve documents by removing unnecessary details, organizing them according to content, highlighting how these characteristics are becoming more relevant and trustworthy, and enabling more accurate context-aware retrieval, which in turn enables more informative context retrievals.

V. DISCUSSION

5.1 Discussion of Findings

Incorporating temporal components into the modeling of searches for changing news archives is supported by our experimental findings. In terms of both static and dynamic relevance assessment criteria, such as Precision@10 and MRR, as well as tMAP, TBP, and LDG@10, the suggested hybrid model outperformed all baseline models. The efficacy of content delivery in relation to the temporal user query intent was highlighted by these modifications. Specifically, the model's enhanced performance was due to its ability to detect latent temporal signals and use them for dynamic ranking. In contexts where time plays a significant role, such as in crisis reporting, politics, and journalism, this suggests that temporal factors are not just important, but crucial, when it comes to retrieving information that is meaningful in context. In addition, the system's improved performance in LDG and TBP shows that it may reduce latency in retrieving relevant information. This increases the model's usefulness in near-real-time settings, such as news monitoring and event tracking systems, and enhances user happiness. Examining the relevance and temporal similarity scores reveals that the model successfully retrieves materials that are particular to a given period. Key events such as the 2020 elections and the COVID-19 pandemic, which have higher temporal similarity and temporal relevance values, show that the model is good at dealing with time-sensitive inquiries. The results show that time-focused models should be considered an essential feature of modern information retrieval systems, particularly for large-scale archiving systems that hold documents from different eras.

5.2 Study Scope Limitations

This study has promising results, but still faces some notable challenges. The evaluation dataset, for example, may still be domain and region biased even though its temporality is domain-wide. News archives differ in the languages they cover, their structure, and how they are tagged, which negatively impacts the generalizability of the model. Moreover, the model currently operates on the premise that the documents being analysed come with unequivocal timestamps, which is far from reality, especially when dealing with older or inadequately kept archives. Also, while the model attempts to classify a query that contains vague temporal markers like "recent news" or "historical trends," it includes no additional markers, making it fall short in the context of ambiguous temporal references. As for the approach the model takes, it ignores behaviour data associated with other users like clicks, user inactivity time, and time on pages, which could greatly improve temporal intent libraries. Temporal efficiency profiling and time-sensitive ranking layers add complexity and latency to the retrieval pipeline. These components, although they improve performance significantly, also add to the computational overhead. They could be a concern in real-time search environments that require speed and responsiveness.

5.3 Directions for Future Research

Future development may focus on expanding upon and fixing the present model's shortcomings. The aim to utilize user interaction data to learn their preferences over time, which may improve their temporal intent categorization, is one of the most enticing. The inclusion of temporal knowledge graphs has the potential to address context-dependent and underspecified temporal expressions that are relevant to intent recognition and document alignment. Additionally, the model may be expanded to include multimodal and multilingual news archives. This means that references to time can be made in more than one language, or even in media like photos and videos. Another avenue to investigate is the development of temporal search interfaces that are interactive and allow users to specify timelines of events and select temporal parameters in addition to retrieving documents. Lastly, the capacity to foresee user needs within a certain time period will probably cause a change in strategy from search and retrieval to proactive information delivery. Among other areas, journalism, surveillance, and emergency response might all benefit from this kind of modification.

VI. CONCLUSION

The research highlighted efforts towards retrieval procedures that include some temporal information and offered an in-depth investigation of the history of temporal query modeling inside news archives. The suggested hybrid model surpassed competing systems across a number of assessment criteria, including Precision@10, MRR, tMAP, TBP, and LDG.

This was attributed to the model's ability to document relevancy and timeliness concerning user's queries. The model also demonstrated the retrieval capabilities of contextual documents through temporal relevancy alignment. Such findings accentuate the need to consider temporal intent, whether implicit or explicit, if precision is to be improved, particularly within query-sensitive fields such as news reporting. There is no doubt that the results have severe consequences; retrieval systems that incorporate temporal features emerged as being more informative, flexible, and responsive to the needs of the users needing such services. This is especially critical for expansive and sophisticated platforms dealing with digital news as they must master the 'now' and 'what' dynamically. Additionally, this approach reduces delay bias and improves visibility of relevant content, enabling the adoption of more dynamic temporal aware search frameworks. Ultimately, the attempt made within the reported work lays the ground for more comprehensive developments aiming at bridging the existing gap between the relevance of static content and aligned changes in user needs over time. Subsequent work ought to focus on advancing systems that operate with temporal reasoning; such work incorporates the development of feedback responsive systems that adapt based on user interaction with the system.

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