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AI System to Generate Context-Based Answers to Questions from Legal Bibliographic Text in Law Libraries

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ABSTRACT

AI-based Question-Answering (QA) systems offer an efficient means of retrieving information from legal bibliographic datasets. This study proposes a content-based selector model that extracts minimal yet relevant contextual responses to user queries. By incorporating theories of reference service, particularly Bernard F. Vavrek's holistic approach and S.R. Ranganathan's principles, this research contextualises AI-driven solutions within traditional library services. The findings demonstrate the robustness of AI in enhancing reference services, supplementing but not replacing human librarians.

Keywords: QA system; Artificial intelligence; AI-driven library models; Law library; AI based reference service

1. INTRODUCTION

Libraries have evolved from mere repositories of information to service-oriented knowledge hubs. Effective reference services facilitate user access to pertinent legal resources, reducing search time while improving research accuracy. Traditional reference services include document retrieval, bibliography assistance, and referrals to external resources. These services give patrons information based on their needs. Even with the increase and ongoing advancement of technology, the relevance of reference services has not diminished, especially in academic libraries with undergraduate students.

There are advantages and disadvantages when technology simplifies tasks. Technological advancements have influenced the forms and sources of information and the methods and locations for delivering library services. Libraries and their resources have transitioned partially to the digital arena of the World Wide Web. Consequently, library patrons can access resources remotely and through their electronic devices, and several libraries are adopting this shift. These technological advancements have also transformed academic library reference environments[1]. However, human reference services have limitations, including time constraints and staff availability find out that around 33 % of queries to reference librarians are for a particular resource, and about 31 % are related to a particular topic[2].

Currently, AI-based QA systems are receiving increased attention in everyday life criticised the historical tendency to define reference services through quantifiable metrics rather than conceptual understanding[3]. He proposed that reference service should encompass the entire library system, integrating an acquisition, cataloguing, circulation, and physical infrastructure. AI-based QA systems align with this theory by embedding machine learning models within library operations, ensuring seamless access to legal bibliographic materials. Creating an AI-based QA system at the library can minimise physical interaction while ensuring patrons' happiness. An AI-based QA system can alleviate librarians' workload and offer patrons text-based input alternatives. Nonetheless, the AI-based QA system may not address every inquiry, as its primary function is to deliver prompt and precise resolutions to academic queries. Talley studied the use of intelligent agent technology in law libraries to identify the information-seeking patrons' information-seeking behaviour and how law libraries benefited from intelligent agent technology in imparting reference services, information literacy, and circulation techniques[4]. Libraries have just recently started to take steps in terms of research or implementation, even though many services and resources leverage the power of AI.

The future of libraries will undoubtedly be impacted by AI and computer technology, just like in other fields. AI applications focused on libraries aim to raise the standard of library operations in providing reference services. Librarians and AI are mutually beneficial and support one another to give people the finest services possible[5]. The study Wheatley and Hervieux surveyed academic libraries' AI use, focusing on top Canadian and US research universities[6]. The study revealed that while

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some institutions construct AI hubs, there is a lack of awareness or reactivity to the AI trend in the libraries. The lack of library AI research is foreseen, and its use is minimal[7]. Library use of digital technologies and change resistance have long been concerns.

We propose an AI-based QA system machine that can analyse the documents provided as a dataset and answer simple questions based on that. The robustness of QA systems is increasing constantly due to the growing interest of researchers in Deep Learning (DL), Natural Language Processing (NLP) and Information Retrieval (IR).

Research in speech and chat-based QA systems has led to the development of dialogue-based systems like Apple Siri and Amazon Alexa[8-9]. Several challenges have been identified, and solutions have been made[10-12]. Various work has been done on Conversational Question Answering (CQA) also. The main goal of CQA is to measure the understanding ability of a machine regarding a text and answer multiple questions interconnected as conversion.

2. LITERATURE REVIEW

Historically, reference service theories lacked a unified framework. Early theorists, including Samuel S. Green and William Warner Bishop, focused on service intensity rather than conceptual depth[3]. Ranganathan's Five Laws of Library Science, particularly "Save the time of the reader" and "Library is a growing organism," emphasised efficiency and adaptability in reference services[13]. AI-based QA systems resonate with these principles by optimising retrieval speed and dynamically learning from user interactions.

Recent AI-driven library models include:

- **uMentor:** Uses a pre-trained LLaMA-2 model to assist students in academic research[14].
- **Ant Colony Algorithm for Smart Libraries:** Enhances retrieval efficiency in digital repositories[15].
- **Rasa NLU Chatbot:** Provides library patrons with automated assistance in document search[16].

Despite these advancements, chatbots primarily address predefined inquiries. This study proposes an AI-based QA system that extends beyond predefined datasets, offering real-time contextual responses.

We have used the Scopus database for the literature review as Scopus covers a vast range of Journals in Library and Information Science. The search query used for this purpose is:

TITLE ((question AND answer AND library) OR (Chatbot AND library) OR (ai AND qa AND library) OR (information AND retrieval AND library) OR (lib-bot) OR (lib AND qa) OR (lib AND ir)) AND PUBYEAR > 2015 AND PUBYEAR < 2025 AND (LIMIT-TO (LANGUAGE , "English"))

This query resulted in a total of 78 documents. The main information obtained from the Bibliometrix package[17] is presented in Table 1.

Table 1. Main information about data

Description	Results
Main Information About Data	
Timespan	2016:2024
Sources (Journals, Books, etc)	56
Documents	78
Annual growth rate %	1.68
Document average age	4.65
Average citations per doc	6.346
References	1598
Document Contents	
Keywords plus (ID)	441
Author's keywords (DE)	232
Authors	
Authors	156
Authors of single-authored docs	24
Authors Collaboration	
Single-authored docs	25
Co-Authors per Doc	2.42
International co-authorships %	14.1
Document Types	
Article	32
Book	1
Book chapter	3
Conference paper	37
Editorial	2
Erratum, Note & Retracted (each)	1

The studies involving designing and developing an AI-based QA system, Chatbot, or Information Retrieval System for Libraries are included. The papers related to erratum that were retracted are excluded. Then, these 78 documents were reviewed as per the inclusion/exclusion criteria, and around 11 were found relevant to the present study.

uMentor is a virtual mentor technique that uses a pre-trained LLaMA-2 model developed on Vietnamese language datasets to assist students with academic challenges, technology literature exploration, study plans, timetables, and resources.[14] Ahriz, *et al.* presented an AI-based Natural Language (NLP) chatbot to automate IT service management for students, educators, and administrators in the digital workplace[18]. Wang and Zheng used the ant colony algorithm to retrieve digital educational resources in smart libraries efficiently[15]. This work focused on collecting, preprocessing, integrating, feature extracting, and developing a search engine to ascertain the appropriate way to obtain results. Prem et al. implemented a Rasa NLU-based chatbot for library management by answering library users' queries in finding their desired documents[16].

The research presents an AI chatbot based on the BERT algorithm available on mobiles to answer library inquiries. It also incorporates speech-to-text recognition, facilitating both text and voice input. This Chatbot also alerts library staff on library users' queries that it has not answered. This allows the librarians to fine-tune the updated data further for training so that Chatbot can answer these queries in the future[19].

Reinsfelder & O'Hara-Krebs adopted a rule-based method for a chatbot named Springshare[2]. The Chatbot works on the algorithm designed using nested conditional statements providing answers to all expected user questions pre-feeded into the bot system data bank by the library staff. So, the Question-answer with the library user's Chatbot results in the staff's pre-drafted answers. If the Chatbot fails to provide an appropriate answer, the user is requested to submit a query via email.

Lappalainen & Narayanan designed a customised Aisha chatbot utilising ChatGPT API and Python for the Zayed University, UAE library[20]. Aisha offers reference and QA services effectively and promptly beyond library hours. Guides and library websites were used to collect and curation data. Staff collected data from the library website without automation. This also used data from Library FAQs. This design approach functions well for testing or medium scenarios but might cause sluggish performance when working with bigger datasets.

Thalaya & Puritat designed a chat bot called BCNPYLIB CHATBOT, which connects users to their official LINE account through the LINE Messaging API[21]. Google Sheets' database provides answers to queres and utilises Dialog flow to evaluate them. This ensures the availability of a library for users' questions on the resources around the clock. In addition, this also provides the library with insight into the unanswered questions, which can be utilised to prepare efficient responses in the future. The 'Hexabot' chatbot is intended to improve users' library usage experience. Users can browse library materials on computers and other portable devices around the clock without physically visiting the library due to its Facebook Messenger integration and Dialog flow-built design[22].

Bagchi introduces the technology and technical foundations with prospective use in the library for a chatbot using Rasa, an open-source conversational application technology driven by artificial intelligence[23].

Park, *et al.* using a logical framework architecture, conversational QA system, responsive icon, and chat techniques, the research provides simple-to-use services utilising danbee.ai. Additionally, it connects to SNS (Telegram) and uses empirical findings to validate user involvement[24].

It is evident from the literature review that several works have been done to address the 33 % of queries to reference librarians related to a particular resource in libraries. However, However, none has been done to address

Table 2. Information at a glance on available systems

S. No.	Name of the system	Technology (model) used	Used for	Questions & answers predefined
1.	uMentor	LLaMaA-2 model	Book recommendation	Yes
2.	Artificial intelligence-based Chatbot	OpenAI's GPT-4	It support in the university	Yes
3.	Smart library	Ant colony algorithm	Retrieval of digital library resource	Yes
4.	Library book recommender	Rasa NLU conversational chatbot	Book recommendation	Yes
5.	Lib-Bot	BERT based	Question answer	Yes
6.	Rule-based chatbot	Rule-based approach	Library reference service	Yes
7.	Aisha	GPT-3.5-Turbo model	Reference and support service	Partial
8.	BCNPYLIB chatbot	LINE messaging API service, dialogflow	Library books finding & faqs	Yes
9.	Library chatbot	Rasa (open-source conversational software platform)	Reference services	-
10.	Electronic library chatbot	danbee.ai of LG CNS,	Assisting users in finding books & and information from the library website	No
11.	Hexabot	api.ai (Google), Dialogflow	Finding library books	Yes

another 31 % of queries to reference librarians. This work is designed to address this and other later types of query using the proposed AI-based AI-based QA system machine.

3. QA SYSTEMS

Several techniques exist in QA system modelling.

3.1 Sequential QA Systems

One of them is Sequential (Knowledge Based)-QA systems. The knowledge base acts as a repository for information on structured data, which is used as a data source for managing and sharing purposes; the knowledge graph is the graphical representation of KB[25]. Several NLP applications are performed based on it[26].

3.2 Conversational QA Systems

Conversational QA System produces natural language responses to human inquiries, involving an individual user in a single-turn dialogue[27]. Different kinds of chatbots are examples of such QA systems.

3.3 Generative (BERT-based) QA Systems

Generative (BERT-based) QA systems formulate responses directly derived from the context. This includes many kinds of usage, the most popular of which are Large Language Models (LLM), of which the GPT is a well-known example[28].

When information generation is expected conversationally, Machine Reading Comprehension (MRC) is a real-life example of QA[29]. There are several public databases available in the QA system domain like DrQA +PGNet, FlowDelta, WS-ORConvQA[30-32].

4. METHODOLOGY

The proposed QA system integrates sentence selection algorithms with distance-based matching techniques. This is another paradigm of a QA-based or information retrieval system where semantic sentences from the input dataset are used to serve any query. The formation of the model starts with the preprocessing of the input data:

4.1 Preprocessing

Preprocessing of the proposed work is performed in the following steps:

Step 1: Tokenisation of Dataset - In the proposed QA system, the dataset text is tokenised with an unsupervised algorithm for extracting sentences from the proposed dataset.

Step 2: Text Cleaning - The text for the proposed dataset text and input question part is converted into lowercase, and then first removed the white spaces. After that, stop words are removed from the text to minimise the error. Term Frequency-Inverse Document Frequency (TF-IDF) is performed to increase the words' popularity[33].

4.2 TF-IDF Weighting

In the next step of the proposed work, TF-IDF is performed on both the asked query and the proposed dataset. Inverse Document Frequency enhances word significance within the dataset. Term Frequency is the number of terms of a word appearing in the dataset concerning the total number of words present.

$$TF = \frac{number\ of\ times\ the\ term\ appears\ in\ the\ document}{number\ of\ terms\ in\ the\ document}$$

Inverse Document Frequency: The IDF of a term indicates how rare the term is across the documents in the corpus. Terms that appear in only a small fraction of documents (such as technical jargon) are given higher importance than common words that appear in most documents (like "a," "the," and "and").

$$\text{IDF} = log \frac{number\ of\ the\ documents\ in\ the\ corpus}{The\ number\ of\ documents\ in\ the\ corpus\ contains\ the\ term}$$

So, TF-IDF=TF×IDF

Figure 1 is the pictorial representation of each term in the corpus of the proposed dataset. PCA is performed on the TF-IDF vectors to visualise the TF-IDF values. In the proposed work, PCA with two principal components is considered for visualising the TF-IDF vectors, which reduces the dimension of the TF-IDF vectors[34]. Component 1 is distributed from 0.0 to 0.8, and component 2 is distributed from -0.2 to 0.6, which is described in the figure situated on the extreme left-hand side of the fig. The other four graphs on the right-hand side of the figure are the partial representation of component 2, plotted in the y-axis in the range of -0.2 to 0.0, 0.0 to 0.2, 0.2 to 0.4 and 0.4 to 0.6, respectively.

4.3 Model Design

The model of the proposed QA-based system consists of a Euclidean distance-based similarity heap algorithm where the pre-processed question vector and the vector of the pre-processed dataset are used as two dimensions of the Euclidean distance.

Figure 2 contains the TF-IDF values and Euclidean distance values present in the question vector.

Figure 3 contains TF-IDF values and Euclidean distance values in the dataset vector. Consider two points, DPq and DPd, are from pre-processed question vector and pre-processed dataset vector, respectively:

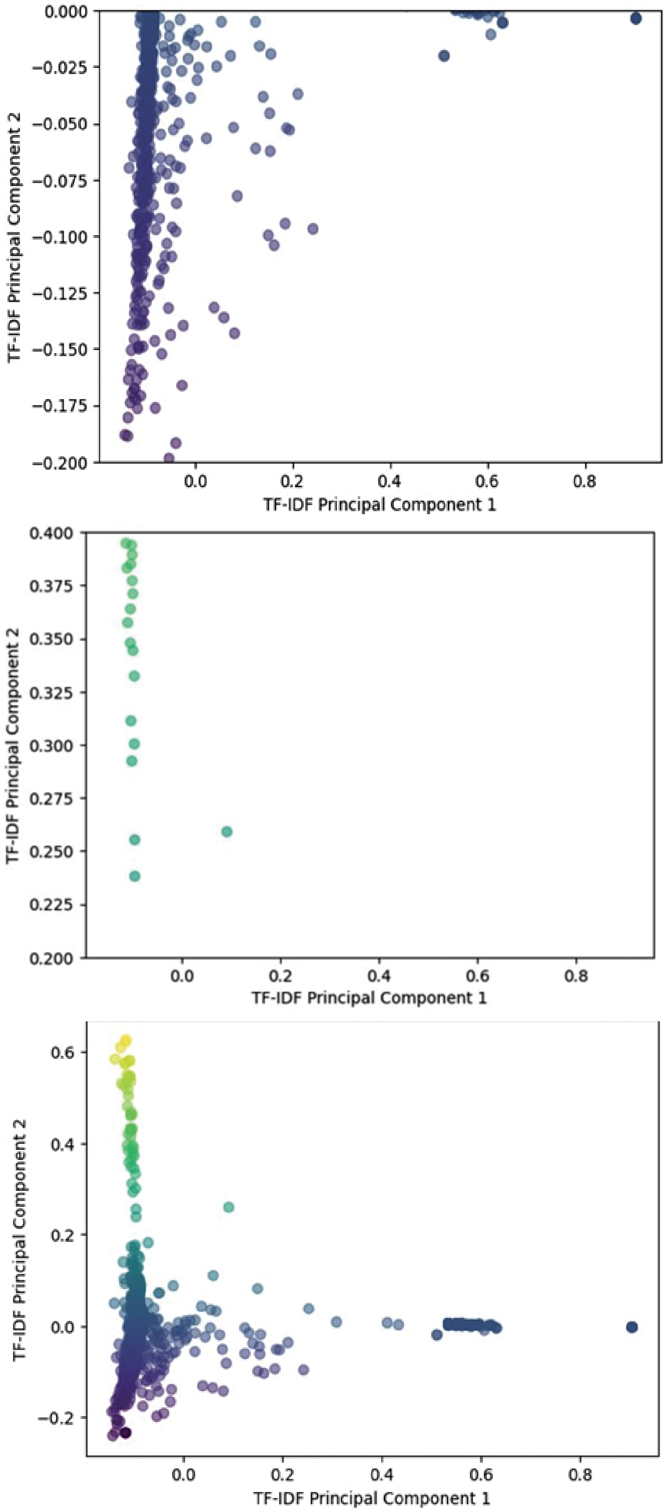
$$DPq = (q1, q2)$$

$$DPd = (d1, d2)$$

So, Euclidean Distance is as follows

$$Edp = \sqrt{(d1 - q1)^2 + (d2 - q2)^2}$$

After finding the Euclidean distance, the resultant sentences are kept in a similarity heap. A threshold is set at four to pick up the best match answer for several asked queries.



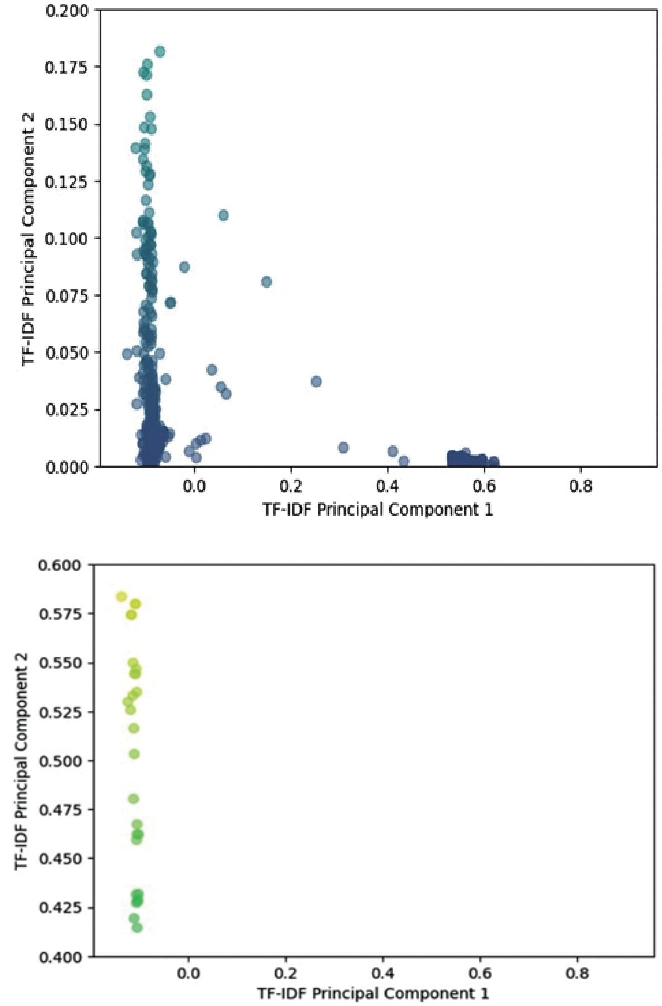


Figure 1. Representation of TF-IDF of words into the corpus of the dataset.

```
Coords         Values
(0, 1344)      0.6824255226414662
(0, 1646)      0.5178032596376299
(0, 1661)      0.40310812213976893
(0, 4503)      0.3219922859652328
```

Figure 2. Samples of pre-processed question vector.

```
(0, 744)      0.06683897325323378
(0, 881)      0.20177780365471862
(0, 980)      0.11393479120350886
(0, 1364)     0.28473225025598015
(0, 1537)     0.20177780365471862
(0, 1661)     0.3137415463625027
(0, 2080)     0.20177780365471862
(0, 2362)     0.173575024609639
(0, 2409)     0.1614408862302994
(0, 2479)     0.20177780365471862
(0, 2715)     0.12048715043359279
(0, 2716)     0.18114984313706492
(0, 2781)     0.10473110104744915
(0, 2866)     0.11056214794426765
(0, 3016)     0.1337903683489289
(0, 3392)     0.173575024609639
(0, 3427)     0.2260861839542325
(0, 3524)     0.19264978571194832
(0, 3563)     0.1861733539138941
(0, 3765)     0.340453580847487
(0, 3958)     0.11845238266116409
```

Figure 3. Samples of pre-processed dataset vector.

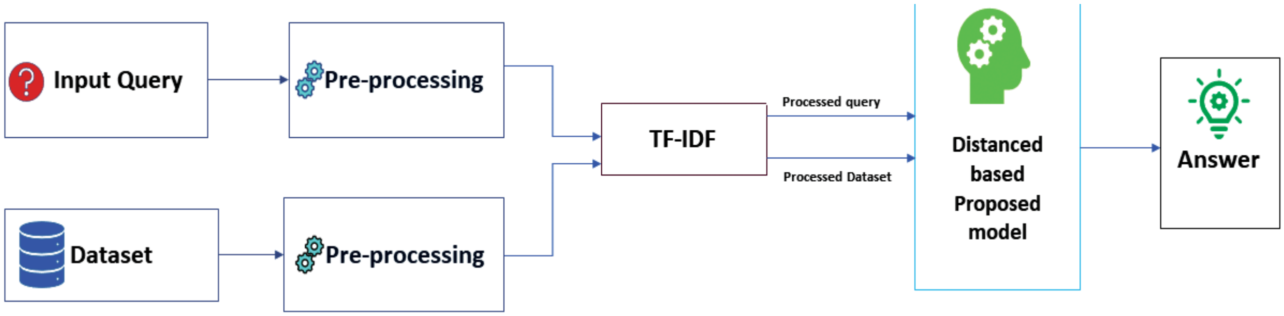


Figure 4. Workflow for the proposed model.

```
Question: What are the classes of Criminal Courts in every State?

Answer is: classes of criminal courts.—besides the high courts and the
courts constituted under any law, other than this sanhita, there shall be,
in every state, the following classes of criminal courts, namely:—
(i) courts of session;
(ii) judicial magistrates of the first class;902
(iii) judicial magistrates of the second class; and
(iv) executive magistrates.
```

```
Question:  When Bharatiya Sakshya bill was introduced in Lok Sabha?
Answer is:
accordingly, a bill, namely, the bharatiya sakshya bill, 2023 was introduced in lok sabha on 11th august, 2023.
```

Figure 5. Screenshot of questions asked to the model and the resultant answers.

5. RESULTS AND DISCUSSION

The dataset used for this proposed work is the entire text of the Bharatiya Nyaya Sanhita, 2023; Bharatiya Sakshya Adhiniyam, 2023 & Bharatiya Nagarik Suraksha Sanhita, 2023.

Fig. 5 is the screenshot of a random query asked to the proposed model and the answers generated from the model.

Fig. 6 is the pictorial representation of the count of sentences with index values present in the similarity heap for the feasible answer to an asked question to the proposed QA model. The purple line indicates the incorporated threshold point of the proposed model.

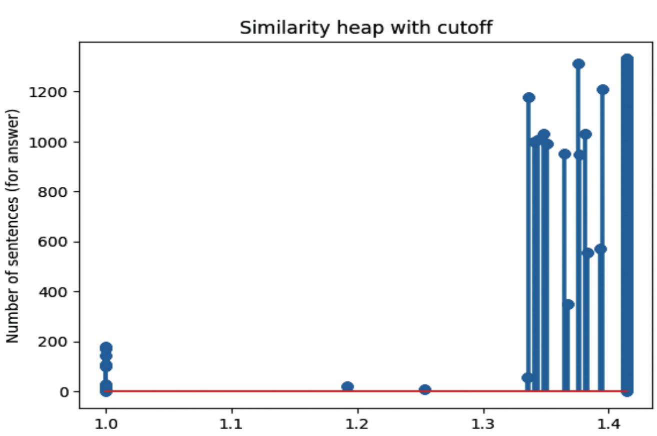


Figure 6. Similarity heap analysis.

6. CONCLUSION

AI-based QA systems offer a scalable solution to reference service limitations. However, complete automation remains infeasible due to the complexity of legal inquiries. Future enhancements will include:

- Integration with External Legal Databases
- Linking with internal legacy bibliographic records
- Voice-Based Interaction Models
- User Profiling for Personalised Assistance

Making libraries' vast resources accessible to all its users. By aligning with Vavrek's and Ranganathan's reference theories, AI-based QA systems can enhance, rather than replace, traditional library services.

User satisfaction and the utilisation of library services may get a boost, providing a more seamless and engaging user experience.

Further, most of the studies are based on conversational chatbots with predefined queries and solutions prepared by library staff for the patrons. They assist the users in finding their desired documents in the library, thus complementing the catalogues. However, this proposed model provides users with answers on a particular topic. This AI-based QA reference librarian is available 24x7 to answer users' questions. Because AI technology constantly functions as a librarian, users can engage with the system anytime.

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