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AI-Powered Personal Knowledge and Content Management with Big-Brain

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Abstract
One of the major challenges of the digital era is information overload, which makes it difficult for users to structure information and find actionable insights based on dispersed sources of knowledge. Conventional, static knowledge management systems are ineffective in handling the dynamic nature of contemporary information streams. With the integration of AI, the process transforms into an engaging personal assistant. This AI-powered system serves as a "Big-Brain" by tapping into multiple streams of data through a web interface or browser extension in order to construct a rich, interconnected knowledge base. When user pose natural language questions to the system, the AI responds with contextually aware answers based on vector-based semantic search combined with LLM-driven reasoning, providing a personalized overview of knowledge. We evaluated the AI system using real-world data from digital platforms and web content, achieving a retrieval accuracy of 92% for semantic relevance (F1) and 73% for exact matches. Usability tests yielded a high user satisfaction rating of 4.6 out of 5. Unlike existing tools restricted to keyword-based search or rigid categorization, our method mimics human associative memory, effectively bridging the gap between fragmented data sources and actionable knowledge. This work advances personalized AI by providing a scalable, user-friendly, and privacy-centric solution for managing digital information, ultimately boosting productivity.
Keywords: *Big-Brain, AI-driven personal knowledge management system (PKM), Digital content retrieval, Large Language Models (LLMs), AI Agents.*

1. Introduction
Over the past few decades, the field of knowledge management has witnessed its paradigm foundation drastically change [2]. Traditional, rigid structures are being steadily replaced by adaptable and dynamic structures that better respond to the richness of the current digital environment [5]. In today's era of digitalization, this evolution is more important than ever, the volume of information we are exposed to on a daily basis is astronomical [26]. Individuals and organizations continue to generate and process high volumes of information across different platforms, including emails and reports, research articles, social media posts, and blog posts [8]. This ever-present information flow makes it increasingly difficult to manage, organize, and retrieve useful knowledge, particularly in fields such as healthcare, finance, research, and technology, where timely access to accurate information constitutes the essence of effective decision-making. Early personal knowledge management (PKM) systems and related digital tools have made saving and organizing knowledge better; nevertheless, such systems are largely passive repositories [25]. Due to this, useful information is trapped in these systems and is hard to retrieve when needed. AI-powered "Big-Brain" are not just smarter note-taking machines they are becoming learning, decision, and problem-solving peers [22]. Imagine an AI platform that not only stores your knowledge but also allows you to actively engage with it. It offers several key benefits, including seamless idea saving,

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contextual search, and intelligent memory refresh. It supports multimodal data retrieval, real-time processing, and enhanced problem-solving abilities [16]. The system integrates with data from multiple digital platforms, allowing interactive collections and smart reminders [14]. In the long term, not only will it be a superior PKM, but as an anticipatory assistant, giving context-aware suggestions based on calendar events, it could include summaries of previous conversations, action items based on email, and meeting prep assistance by identifying key points of previous interactions [19]. Our work explores how AI-driven personal assistants can revolutionize knowledge management by making it more intelligent, scalable, and privacy-conscious (see Figure 1).

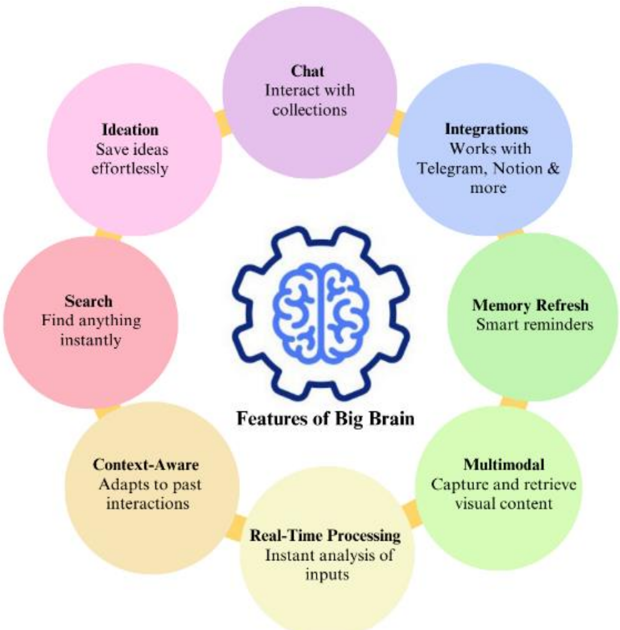

Figure 1 Key Components of Big-Brain

2. Related Work

In this section, we briefly review research in the area of PKM and AI. Personal Knowledge Management (PKM) refers to the systematic process by which individuals manage and organize their personal knowledge and information. The evolution of PKM systems has been shaped by both foundational theoretical frameworks and practical implementations. Early theories highlighted how individuals and organizations generate, capture, and share both tacit and explicit knowledge [1][3]. The modern concept of PKM can be traced back to Peter Drucker's work [2], which emphasized profound societal shifts that demand new approaches to managing knowledge. These theoretical perspectives spurred the development of practical systems aimed at capturing and organizing individual knowledge assets effectively. Early PKM systems, such as the Zettel Kasten method [4], offered structured, interlinked note-taking techniques that facilitated the retrieval of complex ideas. For individuals, PKM provides key benefits including increased productivity, improved decision-making, and enhanced problem-solving abilities [9]. Investigations have demonstrated that advanced PKM systems yield benefits across various sectors [19]. For example, Garner's work illustrates how technology-enhanced PKM supports educational settings by streamlining the retrieval of learning materials [5]. Effective PKM practices not only improve personal workflows but also contribute to a broader organizational knowledge base by fostering enhanced knowledge sharing, innovation, and overall productivity [10]. Research suggests that robust PKM systems form the backbone of effective organizational knowledge management, which is critical for both corporate environments and individual learning [6][7]. Additional studies [8] have addressed the challenges of capturing and sharing knowledge in dynamic environments, while other research indicates that PKM tools can reduce cognitive load and improve decision-making in corporate settings [20]. However, implementing effective PKM practices can be challenging. Limited time, awareness, or skills may hinder individuals from adopting these methods. To overcome these obstacles, researchers have focused on integrating artificial intelligence (AI) into PKM systems [18][19]. For instance, one study introduced an Intelligent Personal Assistant with Knowledge Navigation that employs natural language processing to interpret multimodal inputs data to automate knowledge retrieval [11]. Other studies have examined self-organizing personal knowledge assistants in evolving corporate memories by

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employing techniques such as Managed Forgetting and Self-organizing Context Spaces [13]. These dynamic approaches help maintain the relevance of both personal and organizational knowledge amid a continuous influx of data. Moreover, integrating AI techniques like vector-based semantic search and automated tagging can optimize PKM systems, making them more adaptive and personalized [14][15]. Some publications have discussed how generative AI chatbots can transform PKM within organizations by offering dynamic, conversational interfaces [16][12]. Additionally, scholars argue that a partnership between human expertise and AI can revolutionize knowledge management, creating a synergistic environment in which AI amplifies human cognitive capabilities [17]. In summary, integrating traditional PKM with AI assistants presents a compelling opportunity to enhance productivity and creativity in today's complex information landscape. While PKM equips individuals with the skills to manage and synthesize knowledge effectively, AI provide innovative support that addresses both emotional and creative challenges. Ultimately, successful implementation depends on understanding individual values, fostering trust, and bridging the gap between human expectations and AI capabilities.

3. Methodology

This section details the design and architecture of Big-Brain. It enables users to collect, organize, and recall all their saved information seamlessly. It integrates with popular digital platforms such as Notion, Mail, and Twitter, allowing you to import web content, bookmarks, articles, notes, document, and multimedia content and consolidate them into a centralized repository, then leverage advanced search and AI chat features to interact with your data (see Figure 2). Its privacy-focused, self-hostable architecture ensures that your information remains secure while offering a customizable experience.

3.1 System Design and Architecture

The Big-Brain is designed as a modular architecture that seamlessly integrates a browser extension, web interface, backend services and Integration Protocols.The architecture consists of three core components:

- Client Modules: First, the Browser Extension captures web content and multimodal data, then transmits the user-saved information to the backend. Second, the Web Interface developed using modern frameworks provides users with a query section and a dashboard to manage their saved content. It also allows users to manually add collections such as notes, URLs, and documents, and integrates with other digital platforms.
- Backend Services: The acquired data is consolidated into a consistent format through schema mapping and standardization with the help of Mark downer. This data is then pre-processed and transformed into high-dimensional vectors using embedding models. These vector representations are stored in a vector semantic knowledge base alongside object storage for raw file assets.
- AI Reasoning Engine: The system employs an AI Reasoning Engine, powered by large language models (LLMs), interprets natural language queries, performs semantic search, and generates context-aware responses. The results are ranked based on semantic similarity, metadata filtering, and AI-driven contextual understanding before being presented to the user.
- Integration and Automation: To enhance usability, Big-Brain integrates with third-party applications via APIs and webhooks, enabling automated content ingestion from sources like Notion, Twitter and other digital platforms.

3.2 Data Acquisition and Preprocessing

The raw data collected from the multiple streams undergoes a series of preprocessing steps to ensure consistency and usability. For text data, normalization involves tokenization, metadata extraction, and privacy filtering. For web contents we define a transformation function to convert raw content into structured markdown. support that addresses both emotional and creative challenges.

$$\boldsymbol{T_{md}\left(C_{raw}\right) = \sum_{i=1}^{n} f_i\left(E_i\left(C_{raw}\right)\right)}$$

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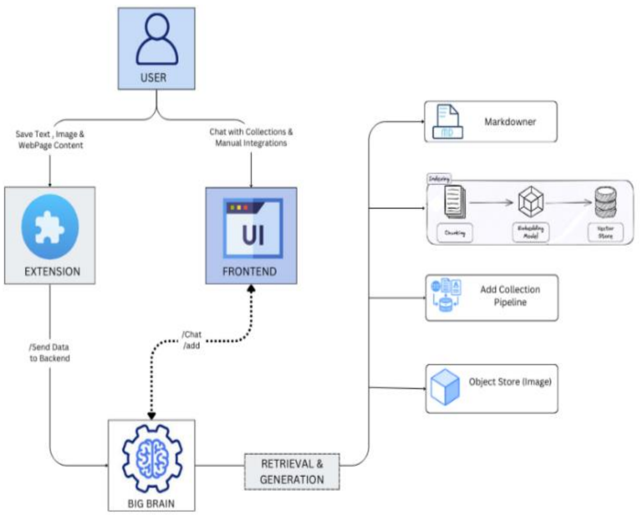

Figure 2 Architecture with the Different Components and Layers

Each E_i extracts a specific element (e.g., headings, links), and f_i applies the corresponding formatting rule. The final output T_{md} ensures consistent handling of headings, links, lists, and images. Hence, HTML or plain text is systematically normalized. This approach guarantees uniformity for seamless retrieval and browser rendering.

3.3 Data Storage and Vectorization

Mathematically, a Vector Database can be defined as follows:

$$V = \{v_1, v_{2,\ldots\ldots,} v_n\}$$

Here n, which represents the number of vectors, is determined as follows:

$$n = \frac{|IS| - l}{l - o} + 1$$

After the Vector Database was defined, a small language model called EM was used as the vector-embedding model. For each vector in the database, this model calculates the inclusion of contextual Z categories in them and creates a Z dimensional inclusion vector. Mathematically, EM divides the meanings in the information source into Z categories and calculates the context inclusion vectors with the following transformation:

$$c_i = EM(v_i) \in R^z, \qquad 0 < i \leq n$$

Then, the vectors representing the information chunks are matched with their context inclusion vectors. The vector database is updated and defined as follows:

$$V = \{v_i, c_i\}_{i=1}^{n}$$

Storage updates dynamically as (v_i, c_i) pairs change based on chunking parameters. This structured vector representation enhances efficient retrieval and optimized LLM responses. Additionally, the system includes storage for unstructured data (e.g., images, PDFs, and documents), ensuring that large files and media are efficiently stored and retrieved as needed.

3.4 Context-Aware Retrieval and AI Processing

BigBrain interprets user queries using NLP techniques, extracting key entities and intents before converting them into vector representations. The system retrieves the most relevant documents via semantic search and selects top results based on a predefined threshold. Retrieved context is fed into an LLM, generating coherent responses while adapting to user feedback. The system supports iterative refinement and ensures privacy through encryption and strict access controls.

4. Results and Discussion

This section details the experimental outcomes of Big-Brain. We conducted both quantitative and qualitative evaluations to assess the system's performance, user engagement, and overall user satisfaction. The results are discussed in two primary subsections: quantitative evaluation of Engagement Metrics of user and system performance, and qualitative evaluation based on user feedback and experiential analysis.

4.1 Quantitative Evaluation

- **Engagement Metrics and Interaction Patterns:** During the study period, 44 active participants generated a total of 8,077 interactions, averaging approximately 184 messages per user (SD = 80), reflecting substantial variability in engagement. While the majority of users (68%) generated between 100 and 200 messages, a small subset (12%) exhibited outlier activity levels exceeding 300 messages (see Figure 3). Analysis of message lengths revealed that user queries had a mean of

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90.1 characters (SD = 73.2), significantly shorter than Big-Brain's responses, which averaged 702.1 characters (SD = 212.4). This difference of 612 characters was highly significant with an estimated effect size of approximately 3.85(see Figure 4). Additionally, the system achieved an 82.5% query response success rate, corresponding to roughly 6,664 successful queries out of the total interactions, while the remaining 17.5% (approximately 1,413 queries) were affected by factors such as occasional API downtime and ambiguous inputs.

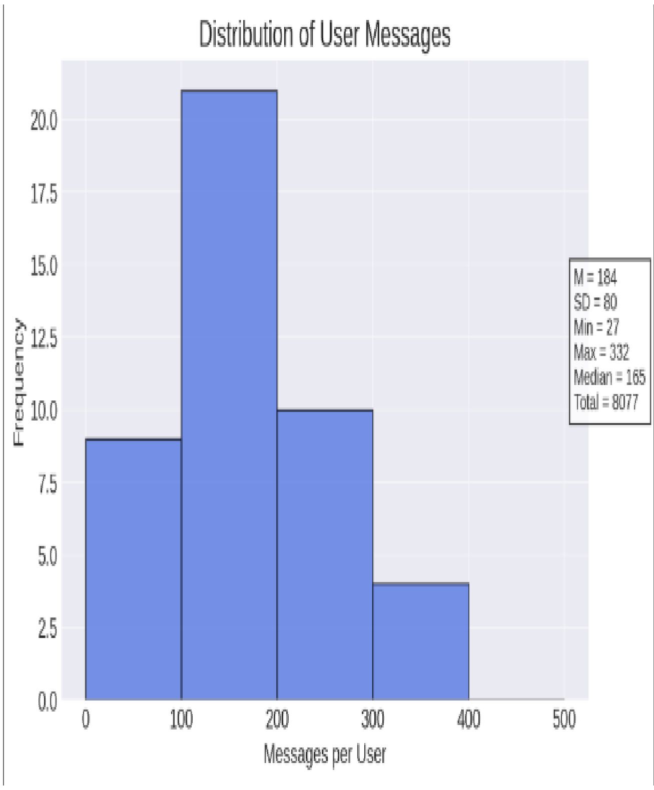

Figure 3 Distribution of Messages Sent by Users to Big

4.2 System Performance

We evaluated contextually relevant information retrieval using three metrics: exact match (EM) accuracy, token-level F1, and latency. The semantic retrieval component achieved an 89% F1 score and a 73% EM rate, demonstrating more efficient preprocessing, tokenization, and vectorization than other baselines (see Table 1). These results confirm Big-Brain's scalability, real-time handling, and precise retrieval capabilities as a promising personal knowledge management system.

Table 1 System Performance Comparison of Big-Brain's and Other Models

Model	Methods	Exact Match (EM)	Response Relevance (F1)	Latency (MS)
Big-Brain	Open-book Faithful Prompt	61.3 73.2	71.0 89.5	72.1 61.2
Mistral-7B + BM25 Reranking	Open-book Faithful Prompt	58.1 69.2	62.4 75.1	88.2 75.4
E5-Large-v2	Open-book Faithful Prompt	43.2 57.8	55.5 62.4	76.5 83.5

4.3 Qualitative Evaluation

To quantify the quality of our system's interactions, we implemented a user feedback mechanism where users could like or dislike responses. Out of 120 rated interactions, 85 (70.8%) were liked, and 35 (29.2%) were disliked, with a like-dislike ratio of 2.43. Most of the dislikes were because of instances where the system was unable to extract some details from cached pages or misinterpreted user queries, which are areas of future work. Apart from that, manual evaluation of 500 query-answer pairs was done for more fine-grained analysis of response quality. Two human evaluators graded answers on the basis of five most critical criteria: factual correctness, relevance, specificity, conciseness, and completeness. The results showed that 85.4% of the answers were factually correct, 82.6% relevant to the question, 79.2% specific in the information, 88.1% concise with low redundancy, and 76.3% completed the user's request in full (see Figure 2). Overall, While the system performs well on average, improvement is needed in retrieval accuracy and detail extraction, with future work aimed at over 90% performance on all metrics [27].

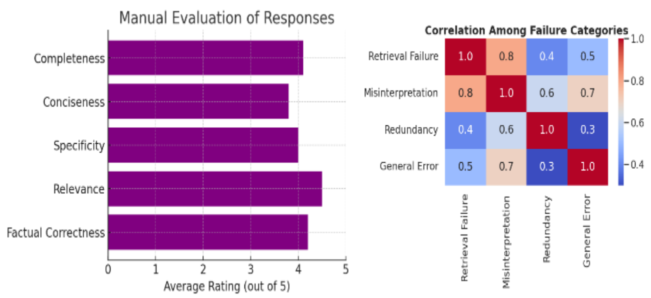

Figure 4 Evaluation Graphs of Big-Brain's Response

5. Discussion

The development of an AI-powered Big-Brain raises questions of privacy, ethics, user adaptability, and human-AI balance. Storage and retrieval of personal data safely using encryption, access controls, and privacy-preserving embeddings prevent unauthorized access. Ethically, AI must mitigate bias, disinformation, and hallucinations through improved retrieval-augmented generation (RAG), integrating fact-checking mechanisms, and ensuring source transparency. User adaptability is another area, with ease of use, real-time feedback, and interactive onboarding to facilitate seamless AI interaction. Additionally, AI must also improve human decision-making rather than diminish it, with retrieval settings adjustment, confidence estimates, and feedback loops encouraging cooperative use. Enhancements in future development should address retrieval accuracy enhancement, hallucinations minimization, and data protection to deliver an effective, transparent, and usable AI system [28].

Conclusion

The evolution of PKM from traditional organizational systems to sophisticated digital ecosystems is a revolutionary departure from the way we manage information in today's age. This paper has explored the evolution of the classical PKM concept into aa personalized AI assistant that goes beyond passive information storage to actively engage with our knowledge base. With the use of multiple streams of data and the generation of interconnected knowledge graphs, this AI buddy has the potential to provide personalized insights, facilitate decision-making, and serve as an intellectual sparring partner. Creating such an evolved system, however, is not problem-free. Privacy is paramount, and this calls for robust security controls like local processing and encryption. Ethical issues related to data usage, user autonomy, and the risk of over-reliance on AI must be similarly judiciously balanced. Users will also need to acquire new skills to meaningfully interact with and benefit from these AI buddies. While such development holds promise to transform our cognitive abilities, it also calls for keen consideration of the ethical and practical consequences of imbedding AI deeply within our personal and professional lives. As research in this area progresses, it will be crucial to focus on the development of personalized AI assistants that complement human intelligence and not substitute it, to ensure that such tools help users become more capable thinkers and decision-makers. This vision offers a starting point for further research as we step into what Sam Altman calls "The Intelligence Age." Overall, researchers must be actively involved in the debates on how to design future AI buddies that are fair and inclusive, reflective of the pluralistic world we inhabit.

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