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Artificial Intelligence in Knowledge Management: Overview and Selection of Software for Automotive Reporting

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Abstract: Knowledge Management is essential for modern organizations, enabling the systematic capture, organization, and sharing of knowledge to enhance decision-making and innovation. Traditional Knowledge Management tools, focused on document storage and retrieval, struggle with unstructured data and collaboration, necessitating advanced technological solutions, particularly those incorporating Artificial Intelligence. - Artificial Intelligence-driven Knowledge Management systems revolutionize data handling through automation, and real-time insights. This is particularly valuable in data-intensive industries like automotive, finance, and healthcare. In the automotive sector, annual reports provide critical insights but are complex and time-consuming to analyze and are a complex example and therefore a good test case. Annual reports of 5 major automotive companies BMW, Volkswagen group, Toyota Motors, General Motors and Tesla were selected as the testing dataset. Artificial Intelligence tools, using natural language processing and machine learning, streamline data extraction. - Despite their benefits, organizations face challenges in selecting the right Artificial Intelligence-driven Knowledge Management software due to a lack of standardized evaluation frameworks. This research applies a systematic methodology for assessing such software, considering usability, adaptability, cost-effectiveness, and data privacy compliance, specifically tailored to automotive reporting and gives recommendation for software tools.

Keywords: Artificial Intelligence; Automotive Reporting; Knowledge Management; Software Assessment; Technology Assessment

1 INTRODUCTION

1.1 Motivation, Objectives & Research Questions

Knowledge management (KM) enhances decision-making and innovation by systematically capturing, organizing, and sharing organizational knowledge. Traditional KM tools struggle with unstructured data and collaboration, necessitating AI-driven solutions. AI significantly enhance productivity, particularly in data-heavy industries like automotive, finance, and healthcare [1]. However, a lack of standardized evaluation frameworks hinders their optimal use [2]. Annual reports are crucial for financial and strategic transparency, especially in the automotive sector, where they guide decision-making and track industry trends and are a complex example and therefore a good test case [3]. Annual reports of 5 major automotive companies BMW, Volkswagen group, Toyota Motors, General Motors and Tesla were selected as the testing dataset. These reports contain extensive data, making manual analysis time-consuming. AI automates content summarization and trend identification, improving efficiency and research quality [4].

This paper gives an overview and selects AI knowledge management software for automative reporting with a systematic methodology based on existing software selection frameworks [5]. The structured approach assesses usability, adaptability, cost-effectiveness, and data privacy compliance, providing insights into optimal tools for analyzing automotive reports and supporting future research and gives a recommendation for tools. This research is going to answer the following research questions

1) What AI driven knowledge management software tools are on the market?
2) How do usability, adaptability, cost-effectiveness, and data privacy compliance impact the selection of AI-driven KM platforms for automotive reporting?
3) What is the most suitable AI-driven Knowledge management software tool for analyzing automotive reports based on the developed evaluation methodology?

1.2 Core Feature & Use Cases of AI Knowledge Management

AI-driven knowledge management (KM) platforms integrate advanced technologies to enhance operations, decision-making, and data insights, playing a crucial role in the automotive sector. Natural Language Processing (NLP) enhances machine understanding of human language using transformer-based models like BERT and GPT, improving semantic search, summarization, and translation [6], [7].

Automated Data Extraction converts unstructured data into structured formats using Named Entity Recognition (NER) and Optical Character Recognition (OCR), reducing human intervention. Predictive Analytics employs machine learning techniques to forecast trends and detect anomalies, aiding risk management and market analysis. Chatbots and Virtual Assistants leverage NLP and frameworks like Rasa to improve knowledge retrieval, streamline onboarding, and support automated help desks [8]. Machine Learning (ML) enables KM platforms to evolve, supporting personalized recommendations, document categorization, and knowledge clustering. Knowledge Graphs use graph databases like Neo4j to map relationships, enhancing search and information discovery. Image and Video Recognition employs convolutional neural networks (CNNs) for multimedia analysis, expanding KM capabilities in visual data-intensive industries [9].

In research and development (R&D), AI-powered platforms like Notion and Guru facilitate knowledge sharing, reducing redundancies and accelerating innovation. AI models like ChatGPT analyze and summarize complex technical documents, improving information retrieval [9]. Predictive analytics aids in forecasting trends and regulatory changes, ensuring strategic alignment [6]. Product lifecycle management (PLM) benefits from AI-driven KM, tracking information from design to maintenance. Predictive analytics anticipates technical issues and identifies enhancement opportunities [9]. Coda integrates with IoT sensors, offering real-time insights into malfunctions, optimizing maintenance and vehicle design [6].

Supply chain optimization relies on AI-driven KM for demand forecasting, risk identification, and procurement decisions. AI analyzes supply chain data, predicts fluctuations, and tracks supplier reliability. Tools like Notion and Guru provide real-time insights into market conditions, minimizing inefficiencies [8]. AI-driven KM automates financial reporting by extracting and summarizing key data from annual reports, reducing manual analysis. NLP scans Management Discussion and Analysis (MD&A) sections for qualitative insights on corporate strategy and market positioning. AI tools track trends across reports, offering insights into financial performance [6].

Strategic risk management benefits from AI-powered KM tools that monitor regulatory changes, supply chain disruptions, and competition. Predictive analytics helps platforms like Guru assess market trends and identify risks before they materialize. AI-driven systems assist compliance teams in tracking regulations across markets, providing actionable compliance insights [9]. These AI-driven KM applications enhance efficiency, decision-making, and risk mitigation, driving innovation and sustainability in the automotive industry [6], [8].

In this context analyzing Automative Reporting with Knowledge Management software as a complex example becomes more and more important in practice and as use case for research.

2 METHOD & APPROACH

To evaluate and compare AI-driven Knowledge Management (KM) tools for analyzing automotive industry reports, a systematic approach was designed. The methodology involves defining the problem, systematically searching for tools, filtering them based on specific criteria, evaluating their capabilities using a weighted decision matrix, and conducting real-world testing for two selected software (see figure 1).

Market research begins with defining the scope of the software search, selecting tools based on KM functionalities, AI-powered features, availability as free/open-source, and positive user ratings. A systematic Google search using predefined keywords ("Knowledge Management Software", "AI-powered Knowledge Management Tools," "Free KM Software", "Top-rated Knowledge Management Platforms") helps document frequently mentioned tools, which is complemented by AI-assisted searches using ChatGPT to retrieve lists of KM software and key attributes. Identifying recurring tools from both sources helps create a refined shortlist. Filtering and screening involve defining criteria related to data processing, search functionality, ease of use, and pricing. Verification methods include cross-checking features via comparison websites, vendor descriptions, and hands-on testing. The elimination process sequentially removes tools failing key requirements, narrowing the selection to the top five for further evaluation (see chapter 3.1).

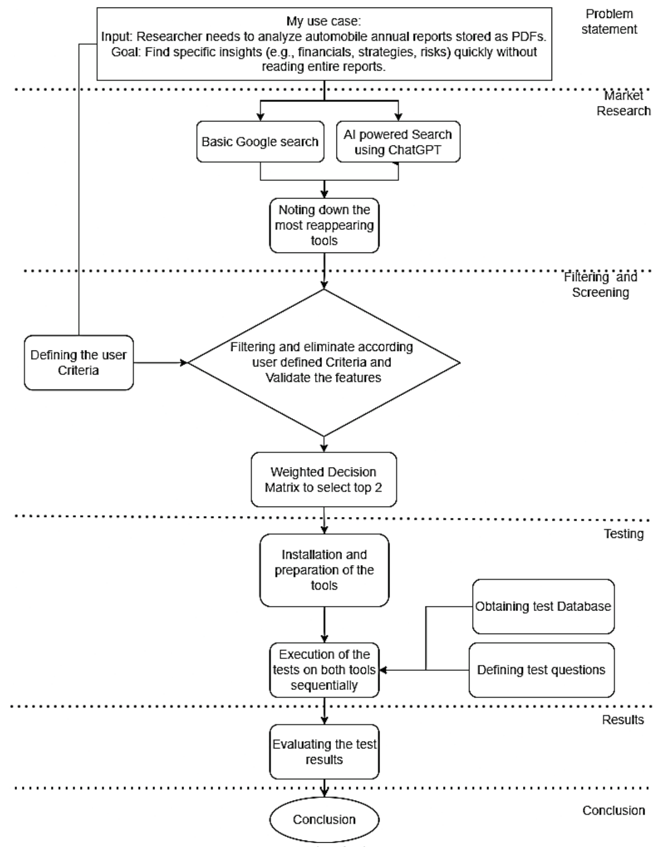

Figure 1 Methodology for Software tool selection

The decision matrix evaluates software using four major criteria: robust AI capabilities (NLP quality, summarization accuracy), ease of use (speed, document handling, offline usability), data privacy (local storage, cloud access permissions), and pricing (free or student-friendly plans). Each tool is rated on a 1–5 scale, weighted (AI Capabilities 50%, Ease of Use 40%, Data Privacy 10%, Pricing 30%), and assessed using a weighted decision matrix to determine the top two tools for real-world testing. Selection of criteria and weightage was done in line with research in this field [5, 25-28] (see chapter 3.2).

The testing phase includes installation, data collection from five automotive companies, and structured queries to assess tool performance in extracting, calculating, and analyzing data. Execution involves document upload assessment, AI-driven query execution, and multi-section analysis. Observation metrics include accuracy (data correctness verification), responsiveness (query processing speed), functionality (document handling efficiency), and limitations/errors (missing features, inaccuracies, usability concerns) (see chapter 3.3).

This structured methodology ensures a thorough, scientific evaluation of AI-powered KM tools for academic and industry research applications.

3 RESULTS: SELECTION OF ARTIFICIAL INTELLIGENCE-DRIVEN SOFTWARE FOR AUTOMOTIVE REPORTING

3.1 Market Research & Filtering

Market research was done to evaluate the most prominent "AI-Driven Knowledge Management Tools. The core of the research was done with a systematic Google search and ChatGPT search with predefined keywords: "Knowledge Management Software", "AI-powered Knowledge Management Tools", "Free KM Software," "Top-rated Knowledge Management Platforms." This search was supported by a literature search of scientific articles about theses software tool in knowledge management. The following software tools could be identified: Confluence, Notion, Guru, Microsoft OneNote, ChatGPT, Coda, Evernote, Obsidian, Glean, Roam Research.

Tab. 1 provides an overview of the software tools identified for further research and corresponding scientific articles.

Table 1 Selected Software Tools for AI-driven Knowledge Management [10-24]

Tool	Description	Scientific Papers (Harvard)
Notion	Highlighted for its seamless integration of databases and task management.	Smith (2020), Brown and Green (2021), Davis (2019)
Guru	Praised for its in-context AI suggestions and automated content improvement.	Johnson (2018), Lee and Kim (2019), Patel (2020)
ChatGPT	Emphasized for generating natural language responses and document summarization.	Zhou et al. (2023), Zhang et al. (2023), Gao et al. (2024)
Coda	Noted for its extensive customization and AI pack integrations.	Newman (2022), Finnegan (2022), McCracken (2018)
Evernote	Lauded for its cross-platform usability and organizational features.	Thompson (2017), Martin and Clark (2018), Roberts (2019)

Confluence, Microsoft OneNote, Obsidian, Glean, Roam Research have been excluded:

Obsidian lacks native support for analyzing text within PDF documents, which limits its applicability for comprehensive document processing. The software requires additional plugins to enable AI-based responses and does not natively support natural language queries. While available for free, optimal utilization necessitates technical configuration, making it less accessible for non-technical users.

Glean is primarily designed for large organizations and does not offer a downloadable standard version for individual users. The software provides personalized solutions rather than a universally accessible standard version, limiting its usability for general knowledge management applications.

Confluence is structured primarily for document sharing rather than in-depth document analysis. It relies on integration with external tools for AI-driven search capabilities and does not return strictly input-based responses. Advanced features are locked behind paid versions, and offline functionality remains limited.

Microsoft OneNote excels in notetaking but lacks advanced text analysis functionalities. It does not incorporate a built-in AI-driven natural language response system. The software does not provide fully functional offline knowledge management capabilities for processing multiple documents simultaneously.

Roam Research is optimized for creating a network of interconnected ideas rather than for processing large sets of documents. The platform does not meet the requirement for input-specific search functionalities. A paid subscription is necessary to access the software, and its user interface presents challenges for non-technical users due to limited ease-of-use features.

3.2 Weighted Decision Matrix to Select Top 2 Software

When selecting the top software platforms for AI-driven knowledge management in the automotive industry, evaluation criteria were weighted based on relevance to the problem statement [25-27]. **Robust AI (40%)** was prioritized as the platform's success depends on AI's ability to process technical and financial language, generate accurate summaries, and adapt to various document formats. **Ease of use (30%)** ranked second due to its impact on adoption and efficiency, ensuring users can focus on insights rather than usability challenges. **Pricing (20%**) was considered important but secondary to AI performance and usability, as long-term benefits outweigh initial costs. Free trials and educational discounts mitigate financial concerns. **Data privacy (10%**) was least weighted since reports analyzed are publicly available, and most platforms already follow strict privacy standards. However, intrusive policies could hinder adoption.

Performing the Weighted Decision Matrix involves evaluating the tools based on the above criteria and assigning scores from 1 to 5 justified by their respective strengths and limitations.

For **Robust AI**, Notion demonstrates strong AI-driven capabilities, including an AI-powered search bar and natural language summarization, though it lacks advanced NLP features like complex calculations and translation, scoring 4. Evernote has powerful OCR functionality but lacks AI search without plugins, scoring 2. Coda excels in summarizing large documents and extracting insights but struggles with comparing multiple sources, scoring 3. ChatGPT leads with its advanced natural language processing, making it the benchmark for AI-driven capabilities, scoring 5. Guru provides AI-driven content suggestions but lacks conversational AI depth, scoring 3.

For **Ease of Use**, Notion has an intuitive interface and automatic PDF-to-text conversion, though the latter is slow, scoring 4. Evernote is known for its straightforward design and offline access, scoring 5. ChatGPT is best for conversational tasks, though document-based workflows require structured prompts, scoring 4. Coda offers customization but requires technical expertise, scoring 2. Guru simplifies knowledge management but is less flexible compared to Notion, prioritizing pre-curated knowledge retrieval over open-ended content creation, scoring 3.

For **Data Privacy**, Notion ensures security with local storage options and encryption, scoring 5. Evernote follows with local storage support, scoring 4. Coda relies on online synchronization and requires an internet connection, though it offers restricted data-sharing options, scoring 2. ChatGPT is cloud-based, which may raise concerns for sensitive data, scoring 2. Guru requires access to external drives and offers no offline functionality, making it less suitable for privacy-conscious users, scoring 1.

For **Pricing**, ChatGPT offers a free version with robust features, requiring a Plus membership for unlimited prompts, scoring 4. Notion provides a student version with sufficient features, though advanced AI functionalities require subscriptions, scoring 4. Evernote has a limited free plan with premium options unlocking more capabilities but still lacking AI, scoring 2. Coda's free version is sufficient for individual users, scoring 5. Guru has limited features in the free version but better pricing for enterprise use, scoring 3.

This analysis highlights the strengths and trade-offs of each tool, allowing for an informed decision based on specific needs and priorities. The summary can be found in Fig. 2. The evaluation matrix revealed that ChatGPT (4.2) and Notion (4.1) scored highest among the tools analyzed, primarily due to their robust AI capabilities and ease of use.

		Notion		Evernote		Coda		Chat GPT		Guru	
Criteria	Weightage (%)	Score	Weighted Score	Score	Weighted Score	Score	Weighted Score	Score	Weighted Score	Score	Weighted Score
Robust AI	40	4	1,6	2	0,8	3	1,2	5	2	3	1,2
Ease of use	30	5	1,5	5	1,5	2	0,6	3	0,9	2	0,6
Pricing	20	4	0,8	2	0,4	5	1	2	0,4	3	0,6
Data privacy	10	3	0,3	2	0,2	3	0,3	4	0,4	3	0,3
	Summation		4,1		3,1		3,6		4,2		2,8

Figure 2 Weighted Decision Matrix for AI Knowledge Management Software

3.3 Detailed Software Testing

The initial phase of the preparation process involved the installation and configuration of the necessary software tools to facilitate AI-driven analysis. Two primary tools were selected: ChatGPT and Notion. A ChatGPT Plus subscription was activated to enable access to GPT-4, providing advanced AI-driven analytical capabilities. The platform was accessed via a web-based interface to ensure seamless usability and integration with other research tools. The Notion application was downloaded and installed in a desktop environment. A student subscription was utilized to access additional AI-assisted features and enhanced operational limits, thereby supporting structured data organization and collaboration. A structured set of evaluation questions was formulated to assess the efficacy of the selected tools in analyzing annual reports within the automotive industry. These questions were designed to capture key dimensions of corporate analysis and were categorized into three fundamental themes:

- financial performance
- investment areas, and
- strategic insights.

Financial performance questions focused on revenue trends, profit margins, cost structures, and liquidity assessments. Investment area inquiries were directed at capital allocation, research and development expenditures, and innovation-driven initiatives. Strategic insights encompassed the analysis of corporate strategies, market positioning, competitive advantages, and sustainability measures.

The selection of these themes ensures a comprehensive evaluation of AI-driven tools' ability to extract, synthesize, and interpret complex financial and strategic data. Tab. 2 summarizes the questions, their difficulty, reason/importance, the challenge for AI and a potential time saving in min compared to a manual execution.

Table 2 Overview of Questions and their Impact on testing the tools

Question	Difficulty	Reason	Challenge for AI	Time Saving in min
Earnings Per Share	Basic	Key profitability metric; widely reported	Avoid extracting diluted/adjusted EPS; locating in charts, tables, or text	5–10
Return on Equity	Medium	Measures shareholder returns	Extracting net income, equity from different sections; calculating average equity	10–15
Return on Assets	Medium	Assesses asset usage efficiency	Finding net income and total assets; identifying terms like "net profit" or "resources"	10–20
Debt-to-Equity Ratio	Medium	Indicates financial leverage	Separating short/long-term liabilities; extracting equity; calculating ratio accurately	15–25
R&D	Medium	Tracks innovation investments	Finding R&D under operating expenses; identifying narrative mentions	20–30
Sustainability Initiatives	Advanced	Shows ESG commitment	Extracting scattered data; synthesizing qualitative info into measurable insights	30–45
Top Risks	Advanced	Highlights major risks and mitigation	Summarizing dense narratives; separating company risks from industry trends	20–40
Future Products	Advanced	Outlines growth via new products	Extracting from MD&A/CEO letter; separating confirmed and speculative launches	20–30

Annual reports of 5 major automotive companies BMW, Volkswagen group, Toyota Motors, General Motors and

Tesla were selected as the testing dataset. These companies were selected considering the different regions of the worlds, hence different styles of reporting creating a very varied dataset. These reports were used in raw pdf file formats.

The summary of the results is displayed in Tabs. 3 & 4.

Table 3 First part of testing results

Aspect	Chat GPT	Notion
Data Retrieval	Excels in retrieving unstructured data directly from reports, even when spread across multiple sections. However, struggles with tables	Highly effective in retrieving information from well-organized, pre-structured databases.
Summari-zation	Capable of synthesizing dense, complex narratives into concise, meaningful summaries.	Provides summarization features for structured text, but lacks depth for unstructured narratives.
Quantitative Calculation Proficiency Overall	Accuracy (35%) No answer rate (10%) Alternate Answers Rate (45%) performance 80/100	Accuracy (25%) No answer rate (56.25%) Alternate Answers Rate (0%) performance 43.5/100
Qualitative Analysis	Strong in extracting insights, identifying themes, and synthesizing qualitative data into actionable insights. But tries hard to structure the answer and fails to list all required objectives in answers.	Theanswers provided are less paraphrased and relies on returned descriptive answers in more sentences. Delivers more accurately when listing objective answers.
Flexibility	Adapts to diverse document formats and layouts without requiring preprocessing.	Works best when data is pre-organized; struggles with unconventional document formats.
Knowledge Retention	Lacks a persistent memory of previous interactions or documents beyond a single session.	Retains all information in a structured database, enabling long term storage and retrieval.

This study compares ChatGPT and Notion in terms of data retrieval, summarization, quantitative accuracy, qualitative analysis, flexibility, search capabilities, document management, scalability, and adaptability. ChatGPT excels in retrieving unstructured data, synthesizing complex narratives, and handling natural language queries, making it ideal for ad-hoc research tasks. It has higher quantitative accuracy (35%) and a lower no-answer rate (10%) compared to Notion. However, it lacks memory retention, document storage, and structured workflow integration. Notion, on the other hand, is highly effective in managing structured databases, organizing long-term projects, and providing a visually rich interface for document categorization. It ensures better knowledge retention and customization but struggles with unstructured data and unconventional document formats. While ChatGPT is more intuitive and ready-to-use, Notion requires setup and familiarization. Overall, ChatGPT performs better for immediate insights and qualitative synthesis, whereas Notion is more suitable for structured data organization and long-term project management.

Table 4 Second part of testing results

Aspect	Chat GPT	Notion
Search Capabilities	Handles natural language queries effectively, offering quick and accurate responses.	Search functionality relies on database tags and structured keywords for best results.
User Interface	Minimalistic, conversational interface ideal for quick, ad-hoc tasks.	Comprehensive and visually rich interface for organizing tasks, notes, and databases.
Ease of Use	Intuitive and ready-to-use without much setup; minimal learning curve for new users.	Requires initial setup and familiarization, especially for structuring data effectively.
Document Management	Does not allow storing or organizing documents directly; focuses on interactive processing.	Offers robust document management, categorization, and linking capabilities for long-term projects.
Scalability	Handles one-off queries efficiently but lacks tools for large-scale project management.	Excellent for managing large volumes of documents, databases, and tasks over extended periods.
Customi-zation	Limited customization options for workflow integration.	Highly customizable with templates, tags, and relational databases to suit specific workflows.
Security and Privacy	Relies on cloud-based interactions, potentially raising concerns for sensitive data.	Offers more control over data privacy when hosted in private workspaces or secure environments.
Adaptability to Use Case	Well-suited for ad-hoc research tasks and in-depth analysis requiring immediate insights.	Designed for long-term projects requiring systematic organization, structured workflows, and tracking.
Learning Curve	Minimal; easy for users to start without prior experience.	Moderate; requires time to set up databases and workflows effectively.

4 CONCLUSION

This paper successfully applied a systematic methodology for selecting the most suitable software tools for analyzing complex documents, specifically in the context of annual reports in the automotive industry. Annual reports of 5 major automotive companies BMW, Volkswagen group, Toyota Motors, General Motors and Tesla were selected as the testing dataset. These companies were selected considering the different regions of the worlds, hence different styles of reporting creating a very varied dataset. Annual reports are complex and therefore a good test case. By integrating established evaluation frameworks and decision matrices, the proposed approach ensures transparency and reliability in software selection, aligning tools with specific application needs.

But this method depends heavily on the chosen context, user needs, and how criteria are weighted, so minor adjustments can change which software rank highest. Because search engine results and user ratings can vary over time, some software or features may appear or disappear. Additionally, AI capabilities differ with updates or data context, making it hard to generalize findings. Lastly, testing only two software limits the scope of this comparison. Despite these issues, the approach still offers a clear, step-by-step way to justify and compare AI-driven Knowledge Management software.

The evaluation of AI-powered Knowledge Management (KM) software, particularly ChatGPT Plus and Notion, highlighted the strengths and limitations of each tool. ChatGPT Plus excels in processing unstructured data, generating concise summaries, and extracting qualitative insights, making it particularly effective for in-depth, one-time research tasks. On the other hand, Notion provides a structured, collaborative environment, ideal for long-term document management and knowledge organization. While neither tool fully meets all knowledge management needs, their combined capabilities demonstrate the importance of selecting software based on task-specific requirements rather than seeking a one-size-fits-all solution.

Furthermore, the rapid advancements in AI-driven KM tools, including natural language processing, intelligent document parsing, and contextual recommendations, underscore their transformative potential in handling complex, data-heavy reports. The study also emphasized the necessity of adaptable tools, given the diverse reporting styles observed in the automotive sector. AI-powered solutions bridge these gaps by streamlining data extraction, enabling efficient analysis, and reducing cognitive overload for researchers.

Ultimately, this research provides valuable insights into the evolving role of AI in knowledge management, reinforcing the need for strategic software selection in corporate reporting and beyond. The findings offer practical guidance for professionals navigating the complexities of large-scale document analysis, demonstrating how AI-driven Knowledge Management (KM) software can enhance efficiency, decision-making, and research effectiveness.

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