POLITECNICO DI TORINO

MSc in Management Engineering

From Experience to Intelligence: AI as the Corporate Brain

Developing an Intelligent Decision Support System to Preserve and Leverage Organizational Historical Knowledge for Enhanced Decision-Making in Project Management

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Abstract

In project-based organizations, the effective management of knowledge is critical to supporting timely decision-making, sustaining innovation, and minimizing inefficiencies. However, traditional Knowledge Management (KM) systems often struggle to address the complexity, fragmentation, and dynamic pace of project environments. At the same time, Artificial Intelligence (AI) offers promising capabilities for enhancing knowledge processes, yet current applications often lack transparency, contextual understanding, and seamless integration into decision-making workflows.

This thesis presents a conceptual framework for an AI-enhanced Decision Support System (DSS) tailored to the needs of knowledge management in project environments. Developed using the Design Science Research (DSR) methodology, the framework combines foundational DSS architecture with modern AI technologies, including machine learning, natural language processing, and semantic reasoning. It is designed to align with all phases of the KM lifecycle, from knowledge discovery and capture to dissemination, utilization, and learning.

The framework is positioned as a strategic response to key organizational challenges such as knowledge loss, inconsistent decision-making, and limited reuse of past experiences. Through detailed analysis and a wide range of practical use scenarios, the thesis illustrates how such a system can facilitate more intelligent, context-aware, and future-oriented project management practices.

Rather than developing a new AI solution or conducting empirical validation, this research offers a structured and visionary model that reimagines KM as a proactive, integrated function. It contributes both a theoretical foundation and a practical guide for organizations seeking to transform knowledge from a passive asset into an active force for decision support and continuous learning.

1. Introduction

1.1 Background

In today's rapidly evolving business environment, project-based organizations depend profoundly on effective Knowledge Management (KM) to maintain competitive advantage, preserve expertise, and support informed decision-making. Traditionally, KM approaches have emphasized static repositories, documented lessons learned, and isolated databases, which have increasingly proved inadequate due to growing data complexity, distributed teams, and rapid project turnovers [1][2].

At the same time, advances in Artificial Intelligence (AI)—especially through machine learning, semantic analysis, and natural language processing—have emerged as transformative opportunities for managing organizational knowledge. Recent studies emphasize that integrating AI with KM practices can significantly enhance the effectiveness and responsiveness of decision-making processes [3][4].

This thesis stands at the intersection of these two important developments, focusing specifically on designing an AI-enhanced Decision Support System (DSS) that intelligently integrates KM practices into project management environments. The proposed framework aims to ensure real-time, context-aware, and evidence-based decision-making, enhancing organizational learning and preserving critical expertise across projects.

1.2 Context and Importance

Project management inherently involves complex decision-making, which is heavily reliant on timely access to accurate, relevant, and actionable knowledge. Project-based environments often create valuable insights—lessons learned, best practices, risk management strategies, and stakeholder engagement methods—that are critical to ongoing success. Yet, due to the temporary nature of projects, these insights frequently become siloed within individuals, lost in documentation systems, or entirely disappear as employees leave or projects conclude [5].

This phenomenon, commonly referred to as "organizational amnesia," significantly undermines an organization's capacity to learn from past experiences and systematically improve future project outcomes [6][7]. Organizational amnesia contributes directly to repeated mistakes, decreased efficiency, and reduced innovation—ultimately leading to competitive disadvantage.

Effective knowledge retention and transfer practices are therefore imperative, not merely for preventing knowledge loss, but also for enabling proactive and informed decisions based on accumulated organizational wisdom [2]. Recent advancements in AI offer powerful tools to address these KM limitations, enabling dynamic, context-sensitive retrieval and reuse of critical project knowledge, thus directly counteracting organizational forgetting.

However, despite these technological advancements, practical adoption of AI-enhanced KM systems remains limited. Most current solutions still function as isolated tools, lacking integration with organizational processes, governance structures, and human-centric workflows. There remains a critical need for clearly defined, practically adoptable frameworks to bridge this gap.

1.3 Problem Statement

In modern knowledge-intensive project environments, traditional KM systems struggle significantly to meet organizational needs. Typically reliant on static document repositories, manual documentation processes, and departmentally siloed information, these systems fail to provide the necessary responsiveness and integration into daily project decision-making workflows. Consequently, critical knowledge—especially tacit knowledge held by senior personnel—often remains undocumented, inaccessible, or lost entirely when individuals leave the organization [7].

Simultaneously, while the introduction of AI into KM processes promises improved efficiency through capabilities such as automated knowledge capture, predictive analytics, semantic retrieval, and adaptive recommendations, current AI-KM applications often operate as "black-box" solutions. They frequently lack explainability, transparency, and trustworthy integration into dynamic project environments [8][9].

Despite growing consensus that hybrid approaches—those integrating human expertise with advanced AI capabilities—offer the most promise, clearly defined models demonstrating how such systems should be structured and practically implemented remain scarce [1][5]. There is a pressing need for a structured, transparent, and integrated AI-enhanced KM Decision Support System (DSS) specifically tailored to the practical realities and decision-making demands of project managers.

This thesis directly addresses this gap by designing and presenting a practical AI-enhanced DSS framework that effectively integrates AI capabilities into existing KM practices within project environments, thereby preserving critical expertise, countering organizational amnesia, and significantly enhancing decision-making outcomes.

1.4 Research Aim and Objectives

Aim:

The primary aim of this thesis is to design a practical, conceptual framework for an AI-enhanced Decision Support System (DSS) that integrates Artificial Intelligence into traditional Knowledge Management practices, thereby improving real-time, context-aware decision-making and knowledge retention in project management contexts.

Objectives:

Examine existing KM practices in project management: Critically evaluate current methodologies to identify strengths, weaknesses, and knowledge retention limitations affecting decision-making.

Investigate AI capabilities and their integration into KM processes: Analyze AI tools, particularly machine learning, NLP, and semantic analytics, highlighting potential advantages and challenges.

Analyze gaps between traditional KM and AI-driven KM solutions: Explore limitations and integration challenges hindering effective knowledge retention and utilization.

Conceptualize a hybrid KM model: Propose a model combining human expertise with AI capabilities, explicitly designed for integration within DSS architectures.

Design a practical AI-enhanced DSS framework: Provide clear operational structures, process flow diagrams, and real-world scenario applications emphasizing practical utility and implementation readiness.

Critically reflect on contributions, limitations, and practical guidelines: Offer a reflective assessment of the framework's value, constraints, and guidelines for practical adoption and future research.

1.5 Research Questions

This thesis seeks to answer the following critical questions:

1. What are the primary limitations of current KM practices in supporting effective project decision-making and knowledge retention?
2. How can artificial intelligence tools effectively address the specific gaps in traditional KM approaches?
3. What are the key challenges and barriers in deploying AI-powered KM solutions practically within project-based organizations?
4. What structure and elements should a practical, integrated AI-enhanced DSS possess to effectively support hybrid KM in projects?
5. How can such a framework enhance real-time, context-aware, and human-centered decision-making and knowledge preservation within project management?

1.6 Thesis Structure

The remainder of this thesis is structured as follows:

Chapter 2 – Literature Review
Provides a comprehensive review of existing literature on KM, AI, DSS, and their intersection, emphasizing theoretical foundations, research gaps, and current limitations in KM practices within project contexts.

Chapter 3 – Methodology
Outlines the adopted research methodology (design science approach), detailing methodological steps, theoretical grounding, and the systematic development of the proposed AI-enhanced KM DSS framework.

Chapter 4 – Framework Presentation and Practical Application
Presents the developed framework in detail, includes operational flow diagrams, detailed use case scenarios in EPC and broader project environments, and critically discusses practical implications and contributions.

Chapter 5 – Conclusion and Discussion
Summarizes key research findings, highlights theoretical and practical contributions, discusses research limitations transparently, provides clear recommendations for future research, practical guidelines for organizational readiness, and concludes with reflective final remarks.

2. Literature Review

2.1 Knowledge Management in Project Management

In project-based organizations, the transient and unique nature of projects often leads to challenges in capturing, retaining, and reusing knowledge. Effective Knowledge Management (KM) is crucial for enhancing project performance, fostering innovation, and maintaining a competitive edge.

2.1.1 The Role of KM in Project-Based Organizations

KM involves systematically capturing, organizing, sharing, and utilizing knowledge to achieve organizational objectives. In project management, KM facilitates the transfer of lessons learned, best practices, and expertise from one project to another, thereby improving efficiency and reducing the likelihood of repeating past mistakes. Knowledge Management is a key resource enabling projects and organizations to address the challenges of a competitive environment [10].

2.1.2 Established KM Frameworks

Several frameworks have been developed to guide KM practices in organizations. The Project Management Body of Knowledge (PMBOK) outlines processes and knowledge areas essential for effective project management, emphasizing the importance of integrating KM into project processes [11]. Additionally, Nonaka and Takeuchi's SECI model describes the dynamic process of knowledge creation through the interaction of tacit and explicit knowledge, highlighting the importance of socialization, externalization, combination, and internalization in KM[12].

2.1.3 Project-Specific KM Practices

In the context of projects, specific KM practices include conducting lessons learned sessions, maintaining knowledge repositories, and performing post-mortem analyses. These practices aim to capture valuable insights and experiences from completed projects to inform future endeavors. However, the effectiveness of these practices often varies, and challenges such as inadequate documentation and lack of stakeholder engagement can hinder their success. Favoretto and Carvalho emphasize the need for a systematic approach to KM in projects to enhance performance and learning[10].

2.2 Types of Knowledge

In the realm of project management, knowledge is primarily categorized into two forms: **explicit** and **tacit**. Recognizing and managing these knowledge types is essential for fostering organizational learning and enhancing project outcomes.

2.2.1 Explicit Knowledge

Explicit knowledge refers to information that is formal, codified, and easily articulated. It can be readily documented, stored, and shared across the organization. Examples include: Project plans, Technical manuals, Standard operating procedures, Lessons learned reports, etc.

This type of knowledge is accessible and transferable through written documents, databases, and training materials. However, while explicit knowledge is valuable, it often lacks the contextual nuances that come with personal experience.

2.2.2 Tacit Knowledge

Tacit knowledge is personal, context-specific, and challenging to formalize. It encompasses insights, intuitions, and skills developed through individual experiences. In project management, tacit knowledge manifests as: Expert judgment, Problem-solving abilities, Interpersonal skills, Understanding of organizational culture, etc.

Due to its intangible nature, tacit knowledge is often shared through direct interactions, such as mentorship, storytelling, and hands-on training. Effectively capturing and transferring tacit knowledge remains a significant challenge in KM practices.

2.2.3 The SECI Model: Bridging Tacit and Explicit Knowledge

Nonaka and Takeuchi's SECI model (Figure 2.1) outlines a dynamic process for knowledge creation and conversion between tacit and explicit forms. The model comprises four modes:

1. **Socialization (Tacit to Tacit):** Sharing experiences to create new tacit knowledge, such as through joint activities or apprenticeships.
2. **Externalization (Tacit to Explicit):** Articulating tacit knowledge into explicit concepts, often through dialogue or reflection.
3. **Combination (Explicit to Explicit):** Systematically combining different pieces of explicit knowledge, leading to new knowledge sets.
4. **Internalization (Explicit to Tacit):** Absorbing explicit knowledge and embodying it into tacit knowledge through practice.

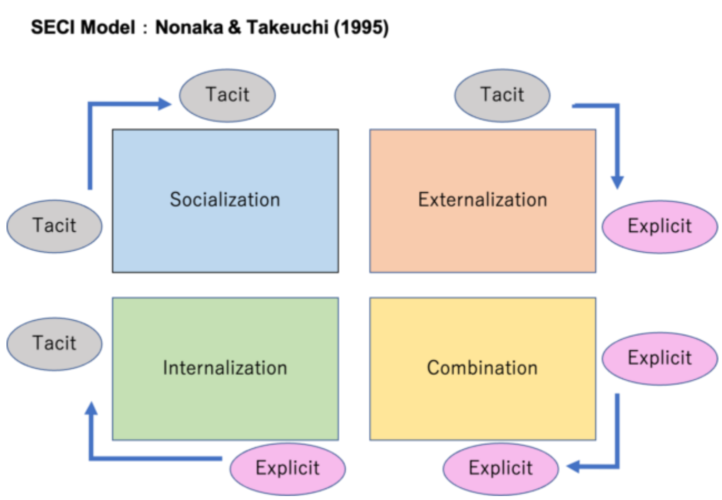

Figure 2.1 - The SECI Model of Knowledge Conversion (Nonaka & Takeuchi, 1995), illustrating four modes of knowledge transformation.

This cyclical process facilitates continuous learning and innovation within organizations.

2.2.4 Importance of Managing Both Knowledge Types

Balancing the management of explicit and tacit knowledge is crucial for project success. While explicit knowledge ensures consistency and standardization, tacit knowledge provides depth and adaptability. Strategies to manage both include:

Codification: Documenting and storing explicit knowledge in accessible repositories.

Personalization: Facilitating interactions and networks to share tacit knowledge.

By integrating these approaches, organizations can enhance knowledge sharing, reduce redundancy, and improve decision-making processes in projects.

2.3 Decision-Making in Project Management and Knowledge Management Integration

2.3.1 Why Knowledge Management is Important for Decision-Making in Project Management

In project-based organizations, decision-making is a daily and critical activity that influences every phase of a project—from initiation and planning to execution and closure. These decisions often occur under conditions of uncertainty and time pressure. The ability to make informed, timely decisions depends on access to reliable knowledge derived from prior projects, subject matter expertise, and organizational context.

Knowledge Management (KM) supports decision-making by ensuring that relevant information—both explicit and tacit—is systematically captured, stored, and made accessible. KM reduces ambiguity and increases decision consistency by transforming individual experiences into institutional knowledge [13]. This is especially crucial in environments where teams rotate frequently, or project contexts evolve rapidly, making continuity and organizational learning essential [14][15].

2.3.2 KM Methods Used in Project Decision-Making

Project managers employ several KM methods to incorporate historical insights and shared expertise into decision-making:

- **Lessons Learned Documentation:** Captures successes and failures post-project and makes them reusable for future initiatives.
- **Knowledge Repositories:** Centralized platforms (e.g., SharePoint, Confluence, PMIS) where project documents, templates, and records are stored and indexed for retrieval.
- **Communities of Practice (CoPs):** Voluntary groups where practitioners across the organization share tacit insights on project risks, strategies, and tools.

- **Project Retrospectives and After-Action Reviews:** Agile and traditional projects alike use structured reflection points to extract knowledge.

- **Expert Networks & Peer Reviews:** Informal or formal consultative forums to validate decisions with experienced colleagues.

- **Knowledge-Based Decision Models (KBDM):** Structured approaches such as KBDM guide decision-making by integrating knowledge review, alternative evaluation, and consensus building [16].

These methods provide a foundation for making not only *faster* but also *wiser* decisions, grounded in collective learning rather than intuition alone.

2.3.3 Best Practices for Effective KM-Supported Decision-Making

While many KM activities are technically in place, their effectiveness varies depending on how they're embedded into project workflows. Best practices include:

- **Embedding KM Tasks into Project Lifecycles:** KM isn't treated as a separate activity but is woven into regular meetings, planning processes, and deliverables.
- **Linking KM to Key Decision Points:** Knowledge is made context-aware by surfacing it at moments where decisions are being made. e.g., during risk assessments or stakeholder analyses.
- **Appointing KM Champions:** Some organizations designate KM leads within project teams who ensure knowledge is captured and utilized appropriately.
- **Using Templates & Taxonomies:** Standard formats and classification structures reduce the cognitive load on users and enhance knowledge reuse.
- **Encouraging a Knowledge-Sharing Culture:** Behavioral norms and leadership support are essential for turning passive documentation into active learning (PMBOK, 2017).

2.3.4 How to Ensure KM Practices Are Working

To ensure that knowledge management (KM) practices are truly effective in supporting decision-making, organizations must go beyond mere implementation and assess their actual impact and utility. One essential approach involves **monitoring usage analytics** to determine how frequently knowledge repositories are accessed, by whom, and for what specific purposes. These metrics can provide early insights into the relevance and accessibility of the system.

Complementing this quantitative assessment, **qualitative feedback from users**, gathered through interviews or surveys, helps to understand the perceived value of KM tools in real-world decision-making scenarios. Furthermore, **linking KM-related metrics to key project performance indicators**, such as cost savings, speed of issue resolution, or overall scope stability, allows organizations to evaluate whether KM practices are delivering tangible benefits.

Finally, conducting periodic **knowledge audits** plays a crucial role in maintaining the health of the system. These audits assess the quality, relevance, and currency of the content to ensure that the knowledge base remains a dynamic and valuable resource, rather than becoming outdated or overloaded with redundant information [16].

2.3.5 Challenges and Gaps in KM-Supported Decision-Making

Despite the recognized benefits, significant limitations persist in practice:

Tacit Knowledge Capture: Tacit knowledge, being highly contextual and personal, often remains undocumented and inaccessible.

Siloed Knowledge: Knowledge is often confined within departments or individuals, limiting its availability for broader use.

Inconsistent KM Adoption: Teams may underuse KM tools due to lack of training, low perceived value, or clunky systems.

Outdated or Irrelevant Content: Repositories can quickly become obsolete if not actively maintained [5].

Lack of Integration with PM Tools: KM platforms often operate separately from project management tools, reducing usability at the point of decision.

Low Real-Time Support: Traditional KM is document-based and static, offering little in the way of interactive, real-time decision support [17].

2.3.6 Issues Faced by Project Managers

Project managers face specific practical difficulties when trying to rely on KM in their daily decision-making:

Time Constraints: Capturing and consulting knowledge is often deprioritized due to time pressures.

Information Overload: Too much content without smart filtering mechanisms can lead to decision fatigue.

Technology Friction: Poorly designed KM interfaces or fragmented systems reduce motivation to engage.

Ambiguous Ownership: Without clear responsibility for maintaining and curating knowledge, quality declines rapidly.

Limited Personalization: Current KM systems often do not adapt to the needs, roles, or contexts of individual decision-makers.

These issues create a clear need for systems that are *intelligent*, *adaptive*, and *context-aware*—setting the stage for the integration of AI technologies, which we explore in the next section.

2.4 Artificial Intelligence in Knowledge Management

2.4.1 Introduction

As knowledge continues to emerge as a core asset in project-based organizations, the need for more intelligent, dynamic, and scalable Knowledge Management (KM) systems is greater than ever. Traditional KM frameworks, although well-established, face growing limitations in keeping up with the increasing volume, variety, and velocity of knowledge generated in modern enterprises [18][19]. Artificial Intelligence (AI) offers a transformative opportunity to rethink how knowledge is captured, retrieved, shared, and applied [20][21].

AI not only accelerates KM processes through automation and intelligent systems but also enables organizations to shift from reactive knowledge use to proactive, insight-driven decision-making. This section outlines the current capabilities of AI as of 2025, maps its role through the DIKW (Data-Information-Knowledge-Wisdom) hierarchy, and explores how it enhances each phase of the KM lifecycle.

2.4.2 Capabilities of AI in 2025

As of 2025, AI technologies have matured far beyond simple automation or prediction tools. They now offer a broad range of functionalities that align seamlessly with KM objectives:

- **Natural Language Processing (NLP):** Enables AI to understand, generate, and interact using human language, facilitating smarter search, summarization, and content generation.
- **Machine Learning (ML):** Allows systems to learn from data without explicit programming, improving knowledge classification, recommendation, and retrieval over time.
- **Reasoning and Inference:** AI can simulate deductive and inductive reasoning, supporting decision-making by connecting disparate knowledge sources and drawing logical conclusions [20].
- **Creativity and Synthesis:** Generative models can now create original content (text, designs, solutions), offering innovative pathways to solve complex problems based on past knowledge.
- **Search and Contextual Awareness:** AI dramatically enhances information retrieval by understanding user intent, context, and relevance, providing not just answers but insight.
- **Personalization and Adaptability:** AI systems adapt to user behaviors and organizational patterns, tailoring knowledge delivery to needs, roles, and preferences [18][19].

These capabilities not only automate KM tasks but enable strategic value creation, making AI a natural extension of the KM function.

2.4.3 The DIKW Hierarchy and Its Relevance to AI-Driven KM

The DIKW hierarchy (**Data, Information, Knowledge, Wisdom**) offers a conceptual model to understand how raw data is transformed into actionable insight [22][12]:

Table 2.1 - Definitions of the DIKW Hierarchy Levels (adapted from Rowley, 2007)

Data	Raw, unstructured facts with no context.
Information	Organized data that begins to have meaning.
Knowledge	Synthesized and contextualized information applicable to specific tasks or decisions.
Wisdom	The ability to make judicious, forward-looking decisions using accumulated knowledge.

AI plays a role at **each layer** of this transformation process: **From Data to Information** --> AI automates data collection, cleaning, tagging, and initial categorization. laying the groundwork for structure and meaning. **From Information to Knowledge** --> AI discovers patterns, clusters, and relationships, enabling the generation of insights and the codification of tacit expertise. **From Knowledge to Wisdom** --> Through predictive analytics, scenario simulation, and recommendation engines, AI supports strategic decision-making and learning from historical knowledge at scale. *(See Figure 2.2)*

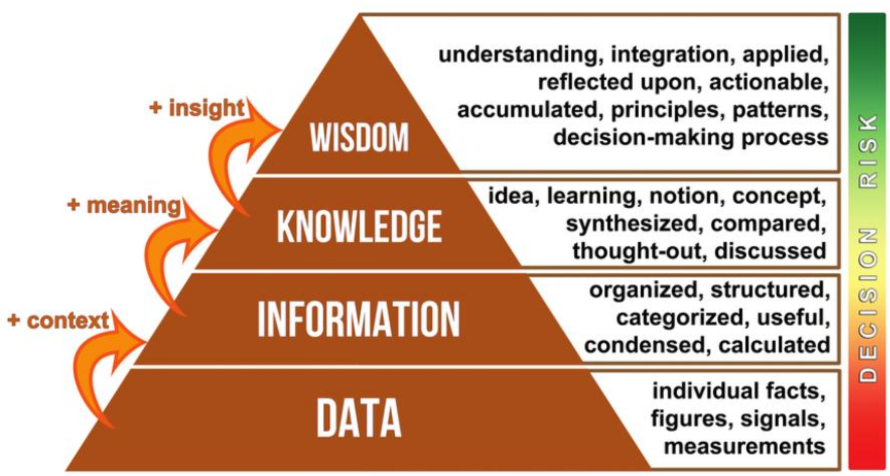

Figure 2.2 - The DIKW hierarchy and AI's role in enhancing each stage of knowledge development, from data to wisdom. AI contributes context, meaning, and insight, enabling advanced decision-making and organizational learning (adapted from Rowley, 2007 and Dalkir, 2011).

Thus, the DIKW model serves as a useful lens for assessing how AI technologies support and elevate each stage of organizational knowledge development.

2.4.4 AI Contributions Across the Knowledge Management Lifecycle

The knowledge management (KM) lifecycle in project-based organizations typically follows five core phases: **Discovery, Creation, Organization, Dissemination,** and **Utilization**. Each of these phases benefits uniquely from artificial intelligence (AI), which enhances knowledge processes by enabling automation, personalization, and real-time contextual support. *(Figure 2.3)*

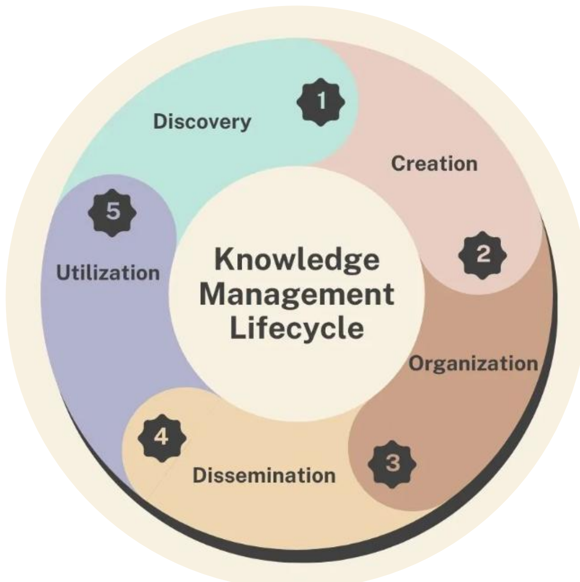

Figure 2.3 - The five core phases of the Knowledge Management (KM) lifecycle in project-based organizations.

1. Knowledge Discovery

Purpose: Identifying existing but often unrecognized knowledge across systems and people.

AI Contributions:

- **Data mining** across emails, project tools, and chats to identify implicit patterns or frequently asked questions.
- **Knowledge gap analysis** using usage logs and content analytics to uncover under-documented areas.
- **Text and semantic analysis** to detect emerging knowledge themes and opportunities.

AI helps organizations surface hidden or underutilized knowledge.

2. Knowledge Creation

Purpose: Generating new knowledge from data, insights, and human experience.

AI Contributions:

- **Real-time capture** from digital interactions (meetings, chat logs, emails).
- **Natural language processing (NLP)** to auto-summarize conversations and extract key points.
- **Machine learning (ML)** to analyze trends, project outcomes, and risk logs for new insight generation.

AI reduces the effort required to transform raw data and informal knowledge into structured, shareable organizational knowledge.

3. Knowledge Organization

Purpose: Structuring and storing knowledge for easy retrieval and alignment with project contexts.

AI Contributions:

- **Auto-classification and tagging** using NLP and contextual inference.
- **Ontology and taxonomy alignment** to maintain consistency across knowledge assets.
- **Semantic search engines** that improve precision and recall by understanding user intent.

These AI capabilities make organizational knowledge more accessible, searchable, and reusable, especially under time pressure. Such tools improve access and reduce time-to-knowledge.

4. Knowledge Dissemination

Purpose: Ensuring the right knowledge reaches the right person at the right time.

AI Contributions:

- **Personalized recommendations** based on project roles, behaviors, and search history.
- **Proactive delivery** of context-relevant knowledge during key decision points.
- **Chatbots and virtual assistants** to support interactive Q&A and knowledge routing.

AI enhances knowledge flow and makes dissemination dynamic, reducing dependency on manual push systems or human gatekeepers. These capabilities facilitate seamless knowledge flow across teams.

5. Knowledge Utilization

Purpose: Applying knowledge to support decisions, solve problems, and enhance performance.

AI Contributions:

- **Decision support systems** offering real-time suggestions, risk insights, and contextual knowledge snippets.
- **Case-based reasoning** for matching current challenges with past project resolutions.
- **Predictive analytics** to support project planning, resource allocation, and stakeholder management.

AI ensures knowledge isn't just stored or shared, but *applied*, helping teams act wisely and proactively, even in uncertain or fast-changing situations. AI enables intelligent application of knowledge at the moment of need.

AI has evolved from being a back-office automation tool to a **central enabler of organizational intelligence**. Its capabilities align with every stage of the KM lifecycle and each level of the DIKW model—enabling not just better data management, but **smarter, context-aware knowledge use**. For project-based organizations, AI-powered KM offers a path to sustained performance, reduced knowledge loss, and evidence-based strategic decision-making.

2.4.5 Practical Tools and Platforms for AI-Enhanced Knowledge Management

While the previous section mapped the theoretical and functional contributions of AI across the KM lifecycle, this section focuses on real-world tools and platforms that operationalize those contributions. These technologies are examples of how organizations are already embedding AI into KM practices to drive knowledge discovery, creation, organization, dissemination, and utilization.

1. Knowledge Discovery Tools

- **IBM Watson Discovery**: An AI-powered search and content analysis platform that helps organizations identify emerging patterns and extract meaning from complex documents.
- **Diffbot**: Uses machine learning and natural language processing to extract structured data from unstructured web sources, helping organizations uncover knowledge gaps and discover market or research insights. (*Figure 2.4)*

Figure 2.4 - IBM Watson Discovery logo – DIFFBOT logo

2. Knowledge Creation Tools

- **Microsoft Viva Topics**: Automatically organizes content and connects related documents across enterprise systems, surfacing contextual knowledge without manual effort.
- **Notion AI**: Assists users in writing, summarizing, and linking content by embedding AI directly into collaborative workspace tools, streamlining the capture and generation of new knowledge. *(Figure 2.5)*

Figure 2.5 – Microsoft Viva topics logo – Notion AI logo

3. Knowledge Organization Tools

- **Guru**: Offers an AI-powered knowledge base that auto-tags, updates, and recommends internal documentation to employees in real time.
- **Qatalog**: Connects tools, people, and knowledge within organizations to deliver precise, AI-curated answers. It enables knowledge alignment across departments.
- **Intergator**: A semantic enterprise search solution that enriches search functionality through contextual metadata and ontology-based classification. (*Figure 2.6)*

Figure 2.6 – Guru logo – Qatalog logo – Integrator logo

4. Knowledge Dissemination Tools

- **Starmind**: Builds a dynamic, self-learning network that connects employees with in-house experts, accelerating knowledge sharing in real time.
- **Zendesk AI**: Enhances service teams' access to knowledge by recommending and retrieving support content based on customer interactions.
- **Atlassian Rovo**: Embeds knowledge discovery and delivery into team workflows, surfacing insights based on project activity and tool integration. *(Figure 2.7)*

Figure 2.7 – Starmind logo – Zendesk AI logo – Atlassian Rovo logo

5. Knowledge Utilization Tools

- **Workato One**: Integrates AI-driven workflow automation with business logic to deliver actionable knowledge in operations, HR, and finance functions.
- **Oxford's AI Drug Discovery Platform**: Used in pharmaceutical R&D to accelerate knowledge-driven decision-making by analyzing vast biomedical datasets.
- **Diffbot Knowledge Graph**: Supports case-based reasoning by providing structured, AI-curated data that organizations can use to inform strategic decisions. *(Figure 2.8)*

Figure 2.8 – Workato One logo – Oxford's AI Drug Discovery Platform log

2.4.6 Conclusion

The growing ecosystem of AI-enhanced KM tools demonstrates that the capabilities outlined in the KM lifecycle are not abstract ideals, but increasingly realizable through off-the-shelf and customizable platforms. These tools provide tangible pathways for organizations to shift from passive knowledge storage to dynamic, context-aware knowledge ecosystems—strengthening their capacity to learn, adapt, and decide with intelligence at scale.

2.5 Decision Support Systems in Knowledge Management and Project Management

2.5.1 Evolution of Decision Support Systems

Decision Support Systems (DSS) originated in the 1970s as computer-based tools designed to assist managers in making structured and semi-structured decisions. Initially reliant on static databases and predefined rules, DSS have evolved to support complex decision-making through data analysis, modeling, and user interaction. Their foundational purpose remains consistent: to support—not replace—human judgment in uncertain, data-rich environments [23].

2.5.2 DSS in Knowledge Management

In the field of Knowledge Management (KM), Decision Support Systems (DSS) function as mediators between information systems and human decision-makers. They facilitate the retrieval and contextualization of organizational knowledge to address specific problems, enabling users to access relevant insights at the point of decision-making. These systems also leverage historical case data and past decision outcomes to inform future strategies, enhancing organizational learning. By integrating explicit knowledge—such as documents and databases—with structured decision models, DSS ensure that valuable organizational knowledge is not merely archived but actively applied. This approach reduces knowledge silos and promotes evidence-based management practices, ultimately contributing to more informed and consistent decision-making processes [24].

2.5.3 Classic Decision Support Systems: Architecture and Components

The traditional DSS architecture consists of three fundamental components *(Figure 2.9)*:

1. DSS Knowledge base (Data Management Subsystem)

This is the central repository of all data the system uses, including **Internal data** from Transaction Processing Systems (TPS), such as financial records, project tracking systems, or operational logs, and **External data** from market intelligence sources, competitor benchmarks, regulations, or public datasets.

The data management subsystem ensures that data is cleaned, structured, and readily accessible for analysis.

2. Model Management Subsystem

This component contains a library of analytical and quantitative models that help process data into actionable insights. These models may include:

- Statistical forecasting models
- Optimization and simulation tools
- Decision trees and sensitivity analysis

This layer is what gives the DSS its *"decision support"* capability by translating raw data into implications, projections, or options for decision-makers.

3. User Interface (Dialog Subsystem)

The user interface allows decision-makers to interact with the system. It supports:

- Query input and scenario setup
- Visualization of results (tables, graphs, dashboards)
- Interpretive tools for scenario comparison or simulation output

A well-designed interface is key to ensuring usability and decision relevance, especially under time constraints.

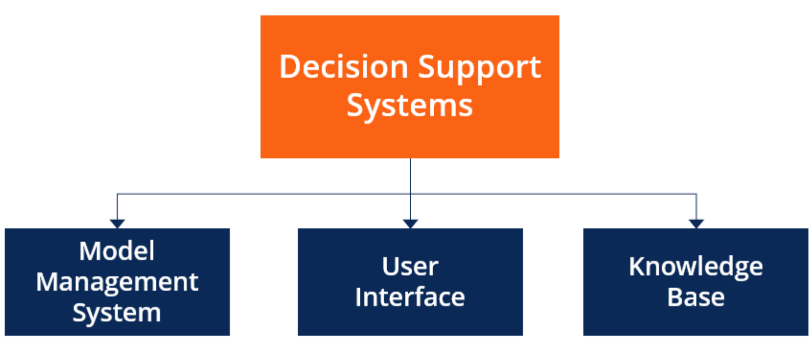

Figure 2.9 - Core components of a Decision Support System (DSS): Model Management System, User Interface (Dialog Subsystem), and Knowledge Base.

How the Classic DSS Works (Flow):

1. **Data from internal systems and external sources** feed into the DSS database.
2. The **model subsystem** processes this data, applying logic and algorithms relevant to the user's decision scenario.
3. The **user interface** displays insights and allows decision-makers to test "what-if" scenarios or drill into data patterns.
4. The **decision-maker** uses this output to guide their actions, often combining it with their own experience and judgment. *(See Figure 2.10)*

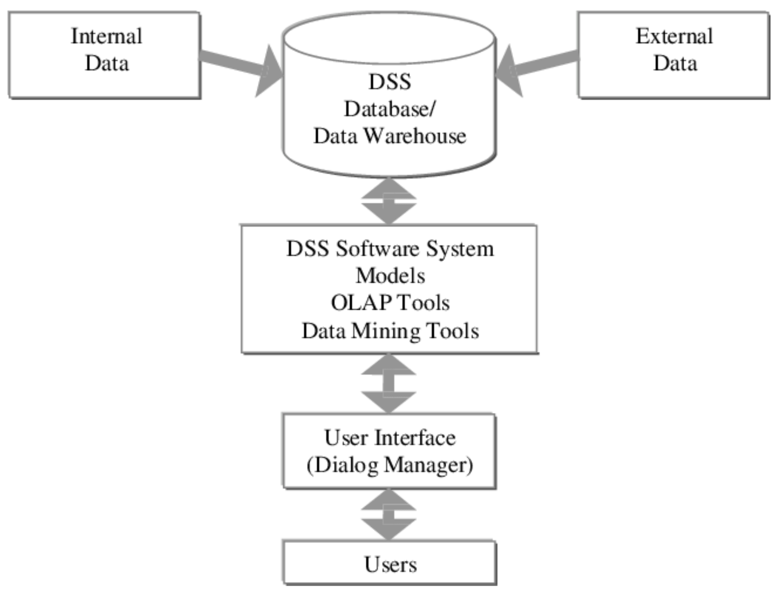

Figure 2.10 - Operational flow of a classic Decision Support System (DSS), illustrating how internal and external data are processed through a model-driven software layer and presented via a user interface to support decision-making.

2.5.3 DSS in Project Management

Project Management (PM) relies on timely, high-quality decisions throughout the project lifecycle. DSS support PM processes by:

- Facilitating cost-benefit analysis, resource allocation, and scheduling decisions.
- Providing visualization tools such as dashboards and project simulators.
- Offering frameworks for scenario analysis and risk mitigation strategies.

These tools are typically integrated into broader project information systems, offering real-time data feeds, performance metrics, and comparative analytics.

2.5.4 Limitations of Conventional DSS

While Decision Support Systems (DSS) offer clear advantages in enhancing project decision-making, several inherent limitations constrain their effectiveness in dynamic project environments. A major drawback lies in their predominantly **static and rule-based architecture**, which tends to be inflexible and unable to adapt quickly to evolving scenarios. Additionally, traditional DSS often **operate solely on structured, explicit information**, thereby excluding the tacit, experience-based knowledge that is frequently embedded within teams.

Another significant limitation is **the reliance on manual data curation**, where inputs and updates require human intervention. This not only introduces the potential for error but also delays the responsiveness of the system. Furthermore, conventional DSS typically **lack context-awareness**, meaning they do not adapt to the specific preferences of users or the shifting nuances of the project environment. Together, these challenges underscore the necessity for more intelligent, adaptive, and knowledge-aware systems; Particularly in project contexts defined by high complexity, stringent time constraints, and frequent uncertainty [25].

2.5.5 Summary

DSS have historically provided a vital link between organizational knowledge and decision-making, particularly in project-driven settings. Their structure allows for rational analysis, comparative evaluation, and documentation of decision processes. However, their static nature and limited integration with informal knowledge flows leave gaps that become more pronounced in dynamic environments. This creates a compelling case for augmenting DSS capabilities—an issue further explored in the next section, which examines how artificial intelligence is being integrated into DSS to address these limitations.

2.6 AI-Enhanced Decision Support Systems: Opportunities and Challenges

The integration of Artificial Intelligence (AI) into Decision Support Systems (DSS) marks a transformative step in the evolution of Knowledge Management (KM) and Project Management (PM). While traditional DSS have long supported decision-makers with structured data access, analytical models, and interactive interfaces, AI-enhanced systems extend these capabilities by offering dynamic, adaptive, and context-aware insights. These intelligent systems leverage machine learning, natural language processing, and reasoning algorithms to uncover patterns, simulate scenarios, and deliver personalized recommendations.

Before examining the unique opportunities and challenges associated with AI-driven DSS, it is important to first review the foundational types of DSS and how they have evolved into today's more sophisticated, AI-augmented designs. This context provides a necessary backdrop for understanding the functional and strategic shift from static, data-centric platforms to intelligent, knowledge-driven decision environments.

2.6.1 Types of Decision Support Systems (DSS)

Decision Support Systems (DSS) have evolved to support a variety of decision-making contexts—ranging from structured analytical tasks to complex, ambiguous problem-solving. Based on foundational work by

Holsapple and Whinston (1996) and Power (2002), DSS can be broadly categorized into six primary types *(See Table 2.2).* Each type supports decision-making in different ways depending on the nature of the decision, the user's needs, and the technological structure [26][23].

Table 2.2 - Types of Decision Support Systems (DSS), categorized by focus, features, use cases, and examples.

DSS Type	***Focus***	***Features***	***Use Case***	***Examples***
Data-Driven	Accessing and manipulating large volumes of structured data.	Query tools, data warehouses, OLAP (Online Analytical Processing).	Financial reporting, inventory analysis.	1. SAP BusinessObjects 2. IBM Cognos Analytics 3. Microsoft Power BI
Model-Driven	Use of mathematical, statistical, or simulation models to support decisions.	What-if analysis, optimization, simulations.	Forecasting, logistics, risk assessment.	1. LINDO 2. Crystal Ball 3. IBM CPLEX Optimization Studio
Knowledge-Driven (Expert Systems)	Providing expert advice based on rules, logic, and knowledge bases.	Rule-based engines, logic trees, knowledge repositories.	Diagnostics, policy compliance, troubleshooting.	1. MYCIN (medical DSS) 2. Dendral 3. FICO Blaze Advisor
Document-Driven	Searching, retrieving, and managing unstructured documents.	Full-text search, document mining, classification.	Legal research, regulatory compliance, case study analysis.	1. Document360 2. SharePoint-based DSS 3. DocuWare
Communication-Driven	Facilitating collaboration and shared decision-making.	Group communication tools, shared workspaces, collaborative filtering.	Project collaboration, distributed decision environments.	1. Zoom + Miro integrations 2. Slack decision bots 3. MS Teams with Planner & Power BI
Web-Based and Enterprise (Hybrid/Integrated)	Integrating multiple types of DSS over the web or enterprise platforms.	Combines data, model, knowledge, and document support in one interface.	Enterprise-level planning, digital transformation initiatives.	1. Oracle BI 2. Salesforce Einstein 3. Qlik Sense 4. Domo

2.6.2 Integration with AI and Knowledge Management

Recent advancements have led to the emergence of **hybrid and AI-enhanced DSS**, often referred to as ***Cognitive DSS***. These systems combine traditional DSS elements with artificial intelligence technologies such as machine learning, natural language processing, and semantic reasoning. In the context of project-based organizations, cognitive DSS are increasingly aligned with Knowledge Management objectives—offering capabilities for dynamic knowledge capture, intelligent retrieval, and contextual application.

The AI-enhanced KM DSS proposed in this thesis reflects this evolution. It integrates knowledge-driven processes with adaptive AI tools to support decision-making in environments where information overload, knowledge loss, and contextual uncertainty are common.

2.6.3 Opportunities of AI-Enhanced DSS

a. Improved Decision-Making Accuracy

AI algorithms can process vast amounts of data to identify patterns and trends that may not be immediately apparent to human analysts. This capability leads to more accurate and informed decision-making processes. For instance, AI-driven DSS can analyze project performance data to predict potential delays or budget overruns, allowing managers to take proactive measures [27].

b. Predictive Analytics and Forecasting

AI enhances DSS by enabling predictive analytics, allowing organizations to anticipate future events and trends. In project management, this means forecasting potential risks and resource needs, thereby improving planning and execution [28].

c. Automation of Routine Tasks

By automating routine and repetitive tasks, AI allows knowledge workers and project managers to focus on more strategic activities. For example, AI can automate data collection and preliminary analysis, reducing the time required for manual processing and minimizing human error [29].

d. Enhanced Knowledge Discovery

AI-powered DSS can sift through unstructured data to uncover valuable insights, facilitating knowledge discovery. In knowledge management, this means extracting actionable information from vast repositories of documents, emails, and other data sources, thereby enhancing organizational learning and innovation [30][31].

2.6.4 Challenges of AI-Enhanced DSS

a. Data Quality and Availability

The effectiveness of AI-driven DSS heavily depends on the quality and availability of data. Poor data quality can negatively impact the accuracy of AI algorithms and limit their ability to provide meaningful insights.

Ensuring access to high-quality data is crucial for the successful implementation of AI-assisted decision-making [8].

b. Complexity and Interpretability of AI Models

Many AI models, particularly deep learning algorithms, operate as "black boxes," making it difficult for users to understand how decisions are made. This lack of transparency can lead to trust issues among decision-makers and may hinder the adoption of AI-enhanced DSS [32].

c. Ethical and Bias Considerations

AI systems can inadvertently perpetuate existing biases present in the training data, leading to unfair or unethical outcomes. Addressing these biases is essential to ensure that AI-enhanced DSS promote equitable decision-making [33].

d. Integration with Existing Systems

Incorporating AI into existing DSS frameworks can be technically challenging and may require significant changes to current infrastructures. Organizations must consider compatibility, scalability, and the potential need for new skill sets among employees to effectively manage and utilize AI-enhanced systems.

e. User Trust and Acceptance

The success of AI-enhanced DSS depends on user trust and acceptance. Decision-makers may be reluctant to rely on AI-generated insights if they do not understand or trust the underlying processes. Ensuring transparency, providing explanations for AI-driven recommendations, and involving users in the development process can help build trust and facilitate acceptance [9].

2.6.5 Implications for Knowledge and Project Management

The integration of AI into DSS has profound implications for KM and PM:

- **For Knowledge Management:** AI-enhanced DSS can transform KM by enabling more efficient data processing, facilitating knowledge discovery, and supporting the creation of more responsive and adaptive knowledge repositories. This transformation leads to a more agile and informed organization capable of leveraging its collective intelligence effectively.
- **For Project Management:** In PM, AI-driven DSS can improve project outcomes by providing predictive analytics, optimizing resource allocation, and enhancing risk management. These systems enable project managers to make data-driven decisions, anticipate challenges, and adapt strategies in real-time, leading to increased project success rates [29].

In conclusion, while AI-enhanced DSS offer significant opportunities to improve decision-making processes in KM and PM, organizations must carefully address the associated challenges. Ensuring data quality, model transparency, ethical considerations, seamless integration, and user acceptance are critical factors for the successful adoption and utilization of AI-driven decision support systems.

2.7 Gaps in Traditional and AI-Driven Knowledge Management

Effective knowledge management (KM) is crucial for organizations aiming to leverage intellectual assets and maintain a competitive edge. While both traditional and AI-driven KM systems have been widely adopted, they exhibit inherent limitations that can impede optimal knowledge utilization. This section explores these shortcomings, emphasizing the need for more integrated and adaptive approaches that can support continuous learning and strategic decision-making.

2.7.1 Limitations of Traditional Knowledge Management Systems

Information Overload

Traditional KM systems often lead to information saturation, overwhelming users and hindering efficient retrieval and decision-making. As repositories expand, organizations struggle with filtering, organizing, and contextualizing relevant knowledge [34].

Static Knowledge Repositories

Many KM systems are structured as static archives, with limited mechanisms for updating or contextualizing knowledge over time. As a result, outdated or irrelevant content accumulates, reducing system usability and trust [35].

Siloed and Poorly Integrated Systems

Traditional KM platforms often function in isolation from other business tools (ERP, CRM), leading to fragmented knowledge and duplicated effort. These disconnected systems limit cross-functional collaboration and hinder holistic decision-making [36].

Inadequate Capture of Tacit Knowledge

Tacit knowledge, rooted in individual experiences and expertise, is challenging to codify and is frequently lost when employees leave or when lessons aren't systematically collected [12]. Conventional KM tools rarely support tacit knowledge exchange effectively.

2.7.2 Challenges in AI-Driven Knowledge Management Systems

Data Privacy and Security Risks

AI-enabled KM systems rely heavily on data collection, raising significant concerns about privacy, consent, and compliance with regulations like GDPR. Improper governance can lead to breaches, misuse, or ethical violations [37][38].

Integration and Implementation Complexity

Incorporating AI into KM is a complex, resource-intensive process. It often involves data standardization, infrastructure upgrades, and employee upskilling—challenges that may deter adoption.

Bias and Ethical Concerns

AI systems can reflect and even amplify existing biases present in training data. In knowledge contexts, this could mean skewed recommendations or exclusion of minority perspectives—thus compromising inclusiveness and fairness [33].

Lack of Human-Centric Communication

AI lacks emotional intelligence and contextual sensitivity inherent to human communication. This can hinder tacit knowledge exchange, reduce engagement, and lead to misinterpretation in collaborative environments [9].

Overdependence and Diminished Human Judgment

As users grow comfortable with AI-suggested actions, they may neglect critical evaluation or defer to algorithmic outputs unquestioningly. This overreliance risks eroding human analytical and reflective skills over time [8].

2.7.3 Bridging the Gaps: Towards a Hybrid Knowledge Management Approach

Overcoming the limitations of both traditional and AI-based KM systems calls for a hybrid approach—one that combines human expertise with machine intelligence to foster adaptability, transparency, and learning. Key components of such an approach include:

- **Continuous Learning and Updating:** Dynamic KM systems that evolve with user input, new insights, and real-time feedback.
- **Interoperable Infrastructures:** Seamless integration with business platforms to enable context-rich knowledge delivery.
- **Ethical AI Governance:** Policies that ensure algorithmic transparency, fairness, and accountability.
- **Human-AI Collaboration Interfaces:** Designing systems that facilitate shared decision-making, where AI augments rather than replaces human input.

By strategically blending structured KM practices with AI-driven insights, organizations can cultivate an environment that preserves experience, fosters innovation, and supports high-quality decisions.

2.8 Literature Synthesis, Research Gap, Research Contribution

2.8.1 Literature Synthesis

The preceding analysis of knowledge management (KM), decision support systems (DSS), and artificial intelligence (AI) within project-based environments has highlighted both advances and persistent limitations. Despite substantial progress in these domains individually, there remains a clear fragmentation when it comes to **integrating them into a coherent, context-aware decision support framework**.

Traditional KM systems—relying heavily on static document repositories, rigid taxonomies, and manual knowledge capture—continue to suffer from issues such as **information overload**, poor **interoperability**, and the inability to effectively retain and transfer **tacit knowledge**. These limitations contribute to knowledge silos and loss, particularly in project settings where staff turnover, time constraints, and task complexity are high [35][12][34].

In contrast, AI-driven systems have introduced **automation, scalability, and real-time data processing** to the KM landscape. AI enables semantic search, summarization, and pattern detection across vast knowledge bases. Yet, many of these tools operate in silos or are embedded within narrow applications, without deep integration into **project workflows** or broader DSS frameworks. Moreover, AI-based systems often focus on **technical capabilities**, while neglecting the **human decision-making context** in which knowledge is actually applied [8].

Despite increasing recognition in the literature that a **hybrid approach** is needed; one that blends structured knowledge assets with AI-enabled insights and human expertise. There is **no well-established model** that shows how such integration can be operationalized effectively within **project management decision support** systems.

2.8.2 Research Gap

This situation reveals a critical research gap: the absence of a comprehensive, integrated framework that bridges traditional KM practices with AI-driven capabilities within a dynamic Decision Support System (DSS), specifically designed for project management environments.

This gap exists in the design and deployment of intelligent DSS frameworks that:

- Seamlessly integrate AI tools with KM practices tailored for project environments;
- Leverage historical, contextual, and real-time knowledge in ways that enhance decision relevance and speed;
- Support both **explicit and tacit knowledge** in guiding project decision-making;
- Address the persistent issues of **knowledge loss**, **poor retrieval performance**, and **underutilized organizational memory**.

2.8.3 Contribution of This Research

Addressing the identified gap, this research proposes the design of an AI-enhanced Decision Support System (DSS) framework aimed at strengthening knowledge management practices and improving decision-making efficiency within project-based organizations.

The contribution of this thesis lies in conceptualizing and structuring a hybrid knowledge system that combines the strengths of both traditional KM approaches (structure, codification, reliability) and AI technologies (automation, contextualization, dynamic insights). The framework is designed to operate as *an intelligent corporate brain* — enabling organizations not only to store knowledge but to actively learn, recall, and apply it at critical decision points within projects.

Specifically, the proposed framework will contribute to:

- Enabling proactive, context-aware, and evidence-based decision-making in project environments.
- Enhancing the accessibility, relevance, and dynamic retrieval of both explicit and tacit organizational knowledge.
- Reducing knowledge fragmentation and loss, supporting the retention of critical expertise despite project turnover or staff mobility.
- Operationalizing AI technologies — such as natural language processing, semantic reasoning, and predictive analytics — within DSS architectures specifically adapted to the dynamic demands of project management workflows.

Through this contribution, the thesis advances current knowledge management theory and practice by offering a practical and strategic approach to designing intelligent DSS for hybrid KM. The research provides a foundation for future knowledge systems capable of evolving with organizational needs, fostering continuous learning, and enhancing organizational memory for more resilient, informed, and agile project management.

3. Methodology and Framework Development

3.1 Introduction

This chapter presents the methodological approach adopted for the development of a conceptual framework aimed at enhancing knowledge management (KM) practices and supporting decision-making processes within project management environments.

Building upon the critical gaps identified in the existing literature — including the fragmentation between traditional KM practices, the underutilization of AI capabilities, and the lack of integration between knowledge systems and decision processes — this chapter outlines the structured pathway followed in designing an AI-enhanced Decision Support System (DSS) framework, contributing both to the advancement of knowledge management theory and to the practical enhancement of decision-making processes within project-based organizations.

Given the conceptual and design-oriented nature of this research, a **framework development methodology** has been selected. This approach is particularly suitable for studies aiming to propose new artefacts — such as models, frameworks, or architectures — intended to address organizational challenges and improve managerial practices [39].

The chapter is structured as follows:

- **Section 3.2** describes the research design and methodological approach, justifying the selection of a conceptual framework development strategy.
- **Section 3.3** discusses the selection of a foundational DSS architecture from existing literature, which serves as the starting point for the proposed enhancements.
- **Section 3.4** identifies and categorizes the AI tools and technologies considered most relevant for supporting KM processes in project-based organizations.
- **Section 3.5** presents the framework development process, detailing the integration of AI functionalities into the DSS structure to address the KM limitations identified.
- **Section 3.6** justifies the design choices made, aligning each component of the framework with specific challenges and needs discussed in previous chapters.
- **Section 3.7** discusses the theoretical and practical scope and limitations of the proposed framework.
- **Section 3.8** provides a summary of the chapter and prepares the reader for the subsequent presentation and discussion of the developed framework.

3.2 Research Design and Methodological Approach

This section outlines the research design and methodological approach adopted in this thesis, aiming to develop a conceptual framework for an AI-enhanced Decision Support System (DSS) to improve knowledge management (KM) practices and decision-making efficiency within project management environments.

Given the objective of this study — to propose a new, hybrid framework that bridges traditional KM practices and AI-driven tools within project-based decision-making — the research adopts a **design-oriented methodology** grounded in conceptual framework development.

3.2.1 Methodological Positioning

This research aligns with the principles of ***Design Science Research*** **(DSR)**, a recognized methodology in information systems and management studies for producing innovative artefacts intended to solve identified organizational problems [40].

Design Science Research is particularly suited for the development of frameworks, models, systems, and architectures; contexts where practical solutions must be grounded in existing knowledge but adapted to evolving challenges; and addressing problems that cannot be resolved through observation alone but require construction and creative [39].

3.2.2 Rationale for Method Selection

The choice of a framework development approach is justified by several factors: 1. The gaps identified in existing literature regarding the integration of KM, DSS, and AI in project environments; 2. The need for a structured yet adaptable model that can address the limitations of both traditional KM systems and isolated AI tools; and 3. The nature of the research problem, which calls for a solution-oriented and synthesis-driven methodology rather than empirical testing or model comparison.

This approach allows for the design of a DSS architecture that is firmly grounded in literature-based best practices in KM and DSS, identified pain points and limitations of current systems, and emerging AI capabilities applicable to knowledge capture, retrieval, and decision support.

3.2.3 Research Inputs for Framework Development

The development of the proposed AI-enhanced DSS framework is informed by three main sources of input *(Table 3.1)*:

Table 3.1 - Key research inputs informing the design of the AI-enhanced DSS framework.

Source	Contribution to Framework Design
Literature Review (Chapter 2)	Provides theoretical foundations and identifies gaps in KM, DSS, and AI integration in project management.
Best Practices and Existing Models	Offers structural elements from prior DSS models suitable for adaptation.
AI Tools and Technological Capabilities	Provides contemporary technological possibilities for knowledge capture, retrieval, contextualization, and application.

3.2.4 Methodological Scope and Limitations

It is important to note that this research is conceptual and design-oriented in nature. The framework developed within this thesis remains at a theoretical and architectural level, without empirical testing or implementation within a specific organizational setting.

Future research is recommended to apply, validate, and refine the proposed framework through case studies, expert evaluations, or practical implementations in real-world project environments.

3.3 Selection of a Foundational DSS Architecture

3.3.1 Introduction

To develop an AI-enhanced Decision Support System (DSS) tailored for knowledge management (KM) in project management (PM), it's imperative to ground the design in a robust, well-established DSS architecture. This foundation ensures that the proposed framework is both theoretically sound and practically applicable.

3.3.2 Overview of Prominent DSS Architectures

A review of the foundational Decision Support System (DSS) frameworks is critical to understanding the evolution toward AI-enhanced, knowledge-centric decision platforms. Three seminal contributions to DSS theory are highlighted below: the structural framework by Sprague and Carlson (1982) [41], the extended knowledge integration model by Holsapple and Whinston (1996) [26], and the typology-based classification developed by Power (2002) [23].

a. Sprague and Carlson's DSS Framework (1982)

Components:

- **Database Management System (DBMS):** Manages data storage, retrieval, and organization.
- **Model-Base Management System (MBMS):** Maintains decision models, analytical tools, and simulation frameworks.
- **Dialog Generation and Management System (DGMS):** Facilitates user interaction with the system by managing queries, inputs, and outputs. *(Figure 3.1)*

Strengths	*Limitations*
○ *Provides a **clear modular separation** between data, models, and user interfaces.*	○ ***Limited focus on knowledge integration**; the architecture is data- and model-centric without explicit KM features.*
○ *Emphasizes the **importance of user-system interaction** for decision-making.*	○ ***Lacks provisions for AI integration**, as it predates modern intelligent systems.*

Visual Representation:

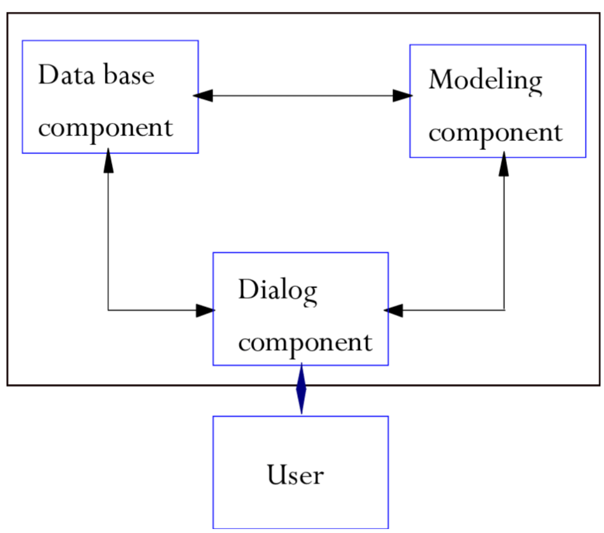

Figure 3.1 - Visual representation of Sprague and Carlson’s (1982) Decision Support System architecture, composed of the Database Management System (DBMS), Model-Base Management System (MBMS), and Dialog Generation and Management System (DGMS). The structure emphasizes modular separation and user-system interaction.

b. Holsapple and Whinston's Extended Framework (1996)

Components:

- **Knowledge Management Subsystem:** Stores organizational knowledge, inference rules, and decision heuristics.
- **Data Management Subsystem:** Manages internal and external data sources.
- **Model Management Subsystem:** Maintains and executes decision models and analytical tools.
- **User Interface Subsystem:** Serves as the medium for user interaction, enabling intuitive access to models, data, and knowledge. *(Figure 3.2)*

Strengths	***Limitations***
o ***Integrates knowledge management*** *into the DSS architecture, acknowledging the critical role of organizational expertise.* o ***Supports semi-structured decision-making*** *where data alone is insufficient, and human judgment is vital.*	o ***Complexity in implementation****; managing interactions across multiple subsystems can be technically challenging.* o ***Higher computational demands,*** *especially for knowledge inference engines.*

Visual Representation:

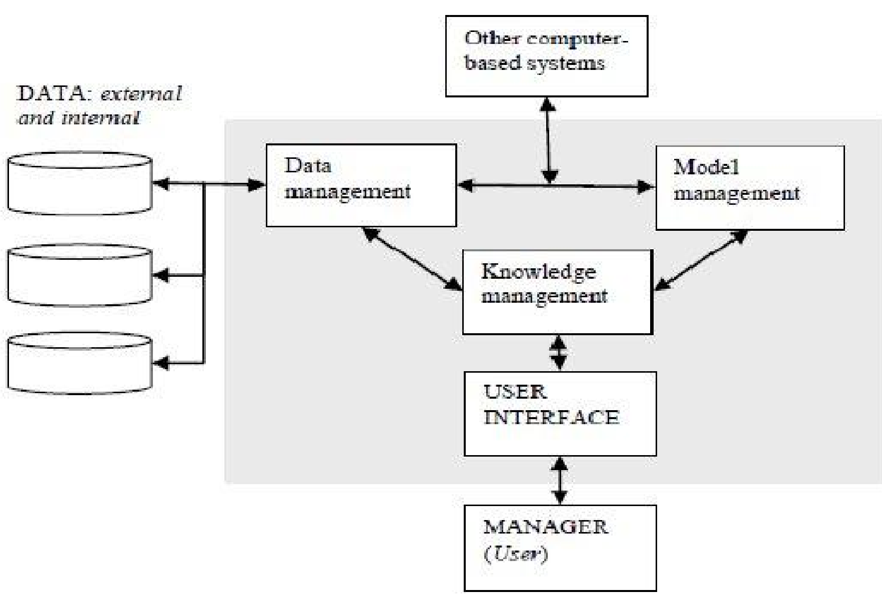

Figure 3.2 - Holsapple and Whinston's (1996) extended DSS framework, incorporating data, model, and knowledge management subsystems, along with a user interface. This architecture supports both structured and semi-structured decision-making through integrated inference and organizational knowledge processing.

c. Power's DSS Typology (2002)

Types:

1. **Data-Driven DSS:** Supports decision-making through access to and manipulation of structured internal and external data.
2. **Model-Driven DSS:** Facilitates decisions by providing access to quantitative models such as simulations, optimizations, or statistical analyses.
3. **Knowledge-Driven DSS:** Offers expert advice or recommendations based on organizational or domain-specific knowledge bases.
4. **Document-Driven DSS:** Assists decision-making through retrieval and management of unstructured textual information.
5. **Communication-Driven DSS:** Enhances collaborative decision-making by enabling communication among group members across locations and platforms.

Strengths	***Limitations***
○ ***Provides a comprehensive classification*** *of DSS based on dominant support mechanisms.* ○ ***Highlights the diversity of DSS applications****, making it adaptable across industries and domains.*	○ *Functions more as a* ***taxonomy*** *rather than a* ***prescriptive architecture*** *for system development.* ○ ***Lacks detailed technical guidance*** *on how to design or implement DSS solutions based on the typology.*

Visual Representation:

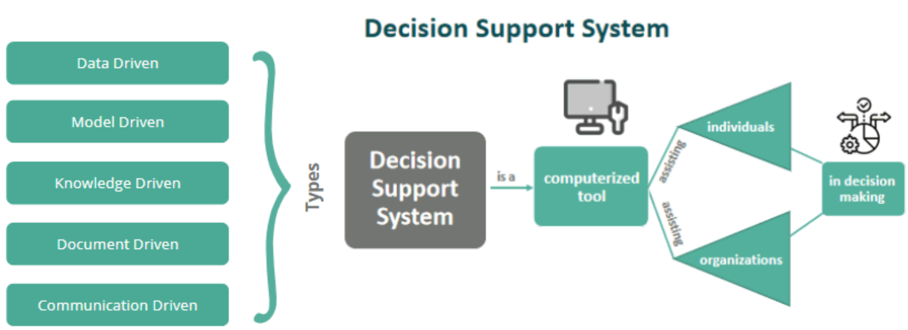

Figure 3.3 - Power's (2002) classification of Decision Support Systems (DSS) by dominant support type: Data-Driven, Model-Driven, Knowledge-Driven, Document-Driven, and Communication-Driven. This taxonomy emphasizes the varied technological and functional mechanisms through which DSS can enhance individual and organizational decision-making.

3.3.3 Architecture Selection

It is important to note that while the selected DSS frameworks originate primarily from earlier decades — particularly the 1980s and 1990s — their foundational structures continue to be highly relevant in current research and practice. This persistence is largely due to their modularity, clarity, and adaptability, which have allowed these models to serve as the conceptual backbone for more recent technological advancements, including AI-driven systems. Contemporary research in DSS rarely proposes entirely new system architectures but instead focuses on extending these classic models with modern technologies such as artificial intelligence, machine learning, and big data analytics [42][23].

Considering the requirements of integrating AI capabilities into KM for PM, **Holsapple and Whinston's Extended Framework** emerges as the most suitable foundation. Its emphasis on knowledge integration aligns well with the objectives of this research. Moreover, its modular design facilitates the incorporation of AI tools, such as machine learning algorithms and natural language processing, into the knowledge base and inference engine components. Therefore, this research adopts Holsapple and Whinston's (1996) framework as a theoretically robust and adaptable starting point, upon which AI-enhanced capabilities for knowledge management in project management environments will be developed.

3.3.4 Adaptation for AI-Enhanced KM in PM

To tailor Holsapple and Whinston's framework for our specific context:

Knowledge Base --> Augment with AI-driven tools for knowledge extraction and representation.

Inference Engine --> Integrate machine learning models to enhance decision-making capabilities.

User Interface --> Develop intuitive interfaces that leverage AI for personalized user experiences.

Model Management System --> Incorporate AI algorithms for dynamic model selection and adaptation.

3.3.5 Conclusion

By adopting and adapting Holsapple and Whinston's Extended Framework, we establish a robust foundation for developing an AI-enhanced DSS tailored for KM in PM. This choice ensures that the proposed system is both grounded in established theory and equipped to leverage modern AI capabilities.

3.4 Identification of AI Tools and Functionalities for Enhancing KM in PM

3.4.1 Introduction

Integrating Artificial Intelligence (AI) into Knowledge Management (KM) processes within Project Management (PM) can significantly enhance decision-making capabilities. This section identifies and categorizes AI tools and functionalities that can be incorporated into the proposed DSS framework to improve KM processes in PM contexts.

3.4.2 Categories of AI Tools for KM in PM

AI tools applicable to KM in PM can be categorized based on their functionalities *(Table 3.2)*:

a. Intelligent Search and Information Retrieval

AI-powered search tools enable efficient retrieval of relevant information from vast organizational data repositories. These tools utilize natural language processing (NLP) and machine learning algorithms to understand user queries and deliver precise results.

b. Automated Knowledge Capture and Organization

AI tools can automatically capture knowledge from various sources, including documents, emails, and meetings, and organize it systematically. This automation reduces manual effort and ensures that valuable knowledge is not lost.

c. Predictive Analytics and Decision Support

Predictive analytics tools leverage AI to analyze historical data and predict future trends, aiding in proactive decision-making. These tools can forecast project risks, resource requirements, and potential bottlenecks.

d. Virtual Assistants and Chatbots

AI-driven virtual assistants and chatbots facilitate real-time information access and support. They can answer queries, provide recommendations, and assist in knowledge dissemination across project teams.

e. Content Summarization and Generation

AI tools can summarize lengthy documents, extract key insights, and even generate content, making it easier for project teams to digest information and create reports or documentation.

Table 3.2 - Categorization of AI tools by functionality and their roles in enhancing knowledge management (KM) in project management (PM) contexts, with examples of widely used platforms.

CATEGORY	ROLE IN KM	EXAMPLE TOOLS
INTELLIGENT SEARCH & RETRIEVAL	Enhancing access to organizational knowledge	Microsoft Azure Cognitive Search, IBM Watson Discovery, Elastic Enterprise Search
AUTOMATED KNOWLEDGE CAPTURE	Capturing and organizing knowledge from various sources	Fireflies.ai (meeting transcripts), Otter.ai, Microsoft Viva Topics
PREDICTIVE ANALYTICS	Risk prediction, project forecasting	IBM SPSS, Azure Machine Learning, Google Vertex AI
VIRTUAL ASSISTANTS & CHATBOTS	Real-time access to knowledge and Q&A	IBM Watson Assistant, Microsoft Power Virtual Agents, Drift AI Chatbots

CONTENT SUMMARIZATION & GENERATION	Summarizing reports, creating knowledge snippets	OpenAI GPT models, Jasper AI, Notion AI

It is worth noting that numerous AI-powered tools and platforms already exist in the market, each offering specific functionalities aligned with the identified KM needs. While the framework proposed in this thesis is not dependent on any particular vendor or solution, awareness of such tools provides valuable insights into the feasibility of implementation. The rapid evolution of AI technologies ensures that organizations have an increasingly diverse toolbox available to operationalize knowledge management enhancements within decision support systems.

3.4.3 Integration of AI Tools into the DSS Framework

Incorporating the identified AI tools into the DSS framework involves:

Table 3.3 - Integration of AI functionalities into the core layers of the proposed DSS framework.

Data Layer	Implementing intelligent search tools to enhance data retrieval capabilities.
Knowledge Layer	Utilizing automated knowledge capture tools to populate and update the knowledge base.
Analytics Layer	Integrating predictive analytics tools to support decision-making processes.
Interface Layer	Deploying virtual assistants and chatbots to facilitate user interaction with the system.
Content Management	Employing content summarization and generation tools to streamline information processing.

3.4.4 Conclusion

The integration of AI tools into KM processes within PM can significantly enhance the efficiency and effectiveness of decision-making. By categorizing and incorporating these tools into the DSS framework, organizations can create a more responsive and intelligent system that supports project success.

3.5 Framework Development of the AI-Enhanced DSS for KM in PM

3.5.1 Introduction

This section presents the development of the proposed AI-enhanced Decision Support System (DSS) framework, designed to improve knowledge management (KM) processes and support effective decision-making within project management (PM) environments.

Building on Holsapple and Whinston's (1996) knowledge-based DSS model, the proposed framework integrates contemporary AI capabilities and adapts system components to address the challenges and gaps identified in the previous chapters.

3.5.2 Design Principles

The development of the framework was guided by a set of core design principles aimed at maximizing both functionality and usability. First, **modularity** was emphasized to allow for the flexible integration of diverse AI tools, ensuring that the system can evolve alongside technological advancements and organizational needs. Second, the principle of **dynamic knowledge flow** ensures that knowledge is continuously captured, updated, and made available in real-time, facilitating responsiveness in fast-paced project environments. The framework also prioritizes **user-centricity**, focusing on creating an intuitive and accessible interface that aligns with the working habits of project managers. Finally, the design comprehensively addresses **coverage of the KM lifecycle**, aligning AI functionalities with all critical phases, including knowledge creation, capture, storage, retrieval, and application.

3.5.3 Core Components of the Framework

The proposed AI-enhanced DSS framework is composed of several interrelated components, each fulfilling a distinct role in supporting knowledge management and decision-making in project environments. These components are embedded with specific AI capabilities to enable intelligent data processing, real-time interaction, and adaptive support throughout the knowledge lifecycle.

Table 3.4 - Core components of the AI-enhanced DSS framework and the corresponding AI functionalities.

Component	Purpose	AI Capabilities Integrated
Knowledge Base	Central repository of structured and unstructured knowledge	NLP for automatic tagging, semantic search, dynamic knowledge graphs
Inference Engine	Supports analysis and decision suggestions	ML-driven analytics, predictive models, pattern recognition

Model Management System	Manages decision models, scenarios, and simulations	AI-powered simulations, recommendation engines
User Interface	Facilitates interaction with the system	AI-driven virtual assistants, natural language interfaces
Knowledge Assets Integration Layer	Entry point for diverse knowledge sources	Intelligent parsing of documents, emails, reports, project logs

3.5.4 Knowledge Assets Mapping within the Framework

As discussed, the AI-enhanced DSS will manage a variety of knowledge assets critical to project management decision-making. The framework envisions specific pathways for capturing and using these assets.

Table 3.5 - Mapping of example knowledge assets within the AI-enhanced DSS framework, including their sources, ingestion methods, and usage for supporting decision-making in project management.

Knowledge Asset	Source	Ingestion into DSS	Usage in DSS
Project Reports	PM software / documents	Automated ingestion & structuring	Lessons learned, project history analysis
Meeting Minutes	Collaboration tools	NLP-based transcription & key points extraction	Decision tracking, knowledge capture
Risk Logs	Risk Management tools	Automated data sync	Predictive analytics, risk assessment
Contracts & Policies	Legal/Compliance databases	Manual upload / automated structuring	Compliance checking, scenario constraints
Emails & Chat Logs	Communication platforms	AI parsing and filtering	Capturing informal but critical knowledge

3.5.5 Visual Representation of the Proposed Framework

The architecture of the proposed AI-enhanced DSS is structured in five interconnected layers. These include data and knowledge sources, an AI-driven processing layer, the DSS core components, a user interaction layer, and the project manager as the decision-making endpoint. This layered design ensures that knowledge flows intelligently from raw data to actionable insights, supporting informed decision-making throughout the project lifecycle. *(Figure 3.4)*

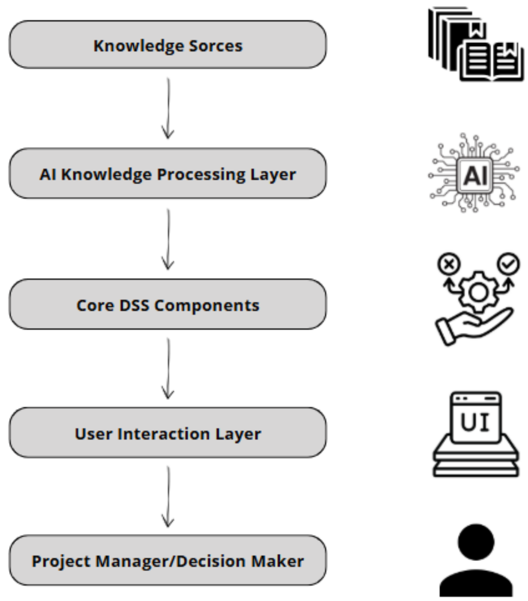

Figure 3.4 - Overall architecture of the AI-enhanced DSS for knowledge management in project management, illustrating the sequential flow from knowledge sources to the decision-maker.

What does this diagram show?

The following table clarifies the function of each layer in the proposed architecture, outlining how knowledge flows from raw inputs to strategic project decision-making.

Table 3.6 - Functional mapping of the AI-enhanced DSS framework layers and their purposes in supporting knowledge-based decision-making.

Layer	***Purpose***
Knowledge Sources	All project-related knowledge assets: reports, emails, lessons learned, logs, risks, contracts
AI Knowledge Processing Layer	AI tools that clean, classify, summarize, extract, recommend knowledge
Core DSS Components	Knowledge base, inference engine, model management, reasoning mechanisms
User Interaction Layer	Virtual assistant, dashboards, semantic search, query handling
Project Manager / Decision-Maker	Final user interacting with knowledge to take decisions

3.5.6 Adaptation Highlights from Holsapple & Whinston

Compared to the original model, this framework introduces several significant advancements. It enhances the Knowledge Base by incorporating AI-powered dynamic capabilities, allowing the system to learn and adapt in real time rather than relying solely on predefined rules. Instead of limiting knowledge assets to static databases, it enables seamless integration with diverse and evolving sources of information. AI is redefined within this framework, not just as a tool for retrieving data, but as an active agent in learning from new inputs, generating insights, and supporting complex decision-making processes. Additionally, the framework places a strong emphasis on usability by incorporating conversational interfaces, making interactions more intuitive and accessible for project managers navigating complex project environments:

- Expands the Knowledge Base with AI-powered dynamic capabilities.
- Integrates knowledge assets far beyond static databases.
- Positions AI not just for data retrieval, but for real-time learning and decision-support.
- Emphasizes user-friendly, conversational interfaces for project managers.

3.5.7 Conclusion

The proposed AI-enhanced DSS framework provides a comprehensive, modular, and adaptive solution for improving knowledge management and decision-making within project management. It bridges existing gaps between traditional KM systems, emerging AI capabilities, and the real-world needs of project environments.

It is important to highlight that while the proposed framework has been designed with a general project management environment in mind, its architecture remains highly adaptable and scalable. The modular design of its components allows for customization based on project size, complexity, industry-specific needs, and the maturity level of knowledge management practices within the organization. Depending on available resources, existing systems, or AI readiness, certain components of the framework can be prioritized, integrated incrementally, or modified to suit particular organizational realities. This flexibility reinforces the framework’s potential applicability across diverse project-driven contexts.

The next section (3.6) will provide a detailed justification of each design choice within the framework.

3.6 Justification of Design Choices

3.6.1 Introduction

This section critically examines the design choices made in developing the AI-enhanced Decision Support System (DSS) framework for Knowledge Management (KM) in Project Management (PM). Each component is evaluated for its relevance and effectiveness in addressing the specific challenges identified in PM contexts.

3.6.2 Alignment with Project Management Challenges

The framework is designed to tackle key issues prevalent in PM:

- **Knowledge Fragmentation**: Projects often suffer from dispersed information across various platforms. The centralized Knowledge Base addresses this by aggregating data, facilitating easier access and retrieval.
- **Dynamic and Uncertain Environments:** The AI Knowledge Processing Layer enables real-time data analysis and contextual awareness, equipping decision-makers to respond swiftly to emerging risks and opportunities.
- **Resource Constraints**: Efficient resource allocation is critical. The Model Management System employs predictive analytics to optimize resource distribution, enhancing project efficiency.
- **Tacit Knowledge Loss:** By integrating diverse knowledge formats (e.g., emails, reports, user discussions), the system preserves critical organizational memory and reduces reliance on individual expertise.

3.6.3 Component Justifications

a. Knowledge Base

Purpose: Serves as the central repository for all project-related information.

Justification: Centralizing knowledge mitigates the risk of information silos, ensuring that all stakeholders have access to consistent and up-to-date information.

b. AI Knowledge Processing Layer

Purpose: Processes and analyzes data to extract actionable insights. (Natural Language Processing (NLP), pattern recognition, semantic analysis)

Justification: By leveraging AI, this layer enhances the ability to identify patterns and trends, supporting proactive decision-making.

c. Core DSS Components

Purpose: Houses the traditional DSS functions, including model management, data access, and rule-based analysis.

Justification: Provides a decision engine that blends AI recommendations with historical knowledge and project data, essential for informed judgment.

d. User Interface

Purpose: Provides an accessible platform for user interaction with the DSS.

Justification: A user-friendly interface ensures that the system is intuitive and accessible, promoting widespread adoption among project teams.

e. Project Manager / Decision Maker

Role: The end-user who interacts with the system to make informed decisions, monitor project health, and implement corrective actions.
Justification: The system is designed to support—not replace—human agency, allowing users to blend AI recommendations with managerial intuition.

3.6.4 Integration of AI Tools

The integration of Artificial Intelligence (AI) tools plays a pivotal role in enhancing the capabilities of the Decision Support System (DSS). Among these, **predictive analytics** is instrumental in supporting forecasting and risk assessment, thereby enabling project teams to adopt more proactive and informed management strategies. Additionally, **natural language processing (NLP)** is leveraged to analyze unstructured data sources—such as meeting transcripts, emails, and project documentation—facilitating the extraction of valuable insights that would otherwise remain untapped. Furthermore, the implementation of **machine learning algorithms** enables the system to continuously refine its decision models by learning from historical data, thereby improving its performance and accuracy over time.

3.6.5 Conclusion

The design choices made in the development of the AI-enhanced DSS framework are strategically aligned with the unique challenges of project management. By integrating AI technologies and focusing on user-centric design, the framework aims to enhance knowledge management practices and support effective decision-making in dynamic project environments.

4. Operationalization and Application of the AI-Enhanced DSS Framework

4.1 Introduction

This chapter presents the operationalization and practical application of the AI-enhanced Decision Support System (DSS) framework developed in the previous chapter. While Chapter 3 focused on the conceptual design of the framework — identifying its core components, underlying structure, and technological integrations — this chapter aims to bring the framework to life by demonstrating how it functions within a project management (PM) environment.

The core objective of this chapter is not merely to describe the framework but to position it within the everyday realities, challenges, and decision-making contexts of project-based organizations. The emphasis is placed on illustrating how the proposed DSS addresses the key problems identified in the earlier stages of this research, particularly those related to knowledge fragmentation, inefficiencies in knowledge retrieval, risk of knowledge loss, and slow or uninformed decision-making processes within projects.

This chapter adopts a highly practical orientation, moving beyond theoretical descriptions to demonstrate:

a. How knowledge flows through the system in real project environments.

b. How artificial intelligence (AI) tools operate within the DSS to support knowledge management (KM).

c. What specific types of knowledge assets interact with the system.

d. How project managers and project teams can engage with the system to enhance their decisions.

e. What practical scenarios and use cases highlight the distinctive value of this framework compared to traditional KM or DSS approaches.

Structure of the Chapter

To achieve these goals, the chapter is structured as follows:

Section 4.2 presents the final version of the AI-enhanced DSS framework, with a particular emphasis on its operational architecture, knowledge flow, and operational dynamics.

Section 4.3 presents practical use scenarios to exemplify how the system operates in real project management contexts, showcasing its added value for project teams.

Section 4.4 offers a critical reflection on the potential benefits, distinctive contributions, and real-world impact of the framework.

Section 4.5 concludes the chapter by summarizing key findings and preparing the way for the next chapter, which will focus on the discussion of results, framework evaluation, and avenues for future research.

4.2 Presentation of the Final Framework

4.2.1 Overview

Building upon the conceptual foundation established in Chapter 3, this section presents the finalized AI-enhanced DSS framework tailored for project management environments. The framework integrates artificial intelligence capabilities to enhance knowledge management and decision-making processes, addressing the challenges identified earlier, such as knowledge fragmentation, decision-making under time constraints, and the need for adaptive learning systems.

4.2.2 Final AI-Enhanced DSS Framework Components

The AI-enhanced DSS framework proposed by this thesis integrates sophisticated artificial intelligence technologies with structured DSS components, providing a robust, intelligent, and context-sensitive solution for Knowledge Management (KM) in Project Management (PM). Building upon the previously established high-level structure, this section provides a detailed view of the core DSS components, explaining their sub-components and interactions clearly.

1. Knowledge Sources

The initial component aggregates multiple data and knowledge inputs, including:

- **Structured Project Data** (e.g., schedules, budgets, KPIs).
- **Unstructured Information** (e.g., emails, reports, meeting notes).
- **External Knowledge** (industry standards, benchmarks, best practices).

This comprehensive aggregation enables thorough context-aware analyses downstream.

2. AI Knowledge Processing Layer

This layer applies advanced AI methodologies, including:

- **Natural Language Processing (NLP)** to transform textual data into structured knowledge.
- **Machine Learning (ML)** algorithms for pattern identification, trend detection, and forecasting.
- **Semantic Analysis** for improving knowledge categorization and extraction.

3. Core DSS Components (AI Enhanced)

This central component is expanded into detailed, interrelated sub-components:

a. Knowledge Base

- A dynamic, continuously updated repository that stores structured insights and historical knowledge.
- Organizes insights according to project phases, contexts, and decision scenarios.

b. Model Management System

- Contains analytic and simulation models to support predictive and prescriptive analyses.
- Allows scenario planning and risk modeling to anticipate and mitigate project risks effectively.

c. Inference Engine

- Implements logic-based reasoning and decision-rule applications.
- Provides automated conclusions and suggestions based on historical patterns and best practices.

d. Decision Recommendation Engine

- Delivers real-time recommendations derived from combined model outputs and inference results.
- Facilitates informed, evidence-based decision-making.

4. User Interaction Layer

A robust, intuitive interface designed for ease of use, ensuring that all insights and recommendations are easily accessible:

- Interactive dashboards summarizing project status and key indicators.
- Natural language query functionality enabling conversational interaction.
- Feedback mechanisms to continually refine and personalize AI recommendations.

5. Project Manager / Decision Maker

The ultimate user, who interacts with the system:

- Uses insights to make informed, contextually appropriate decisions.
- Provides feedback for continuous learning and improvement of the DSS.

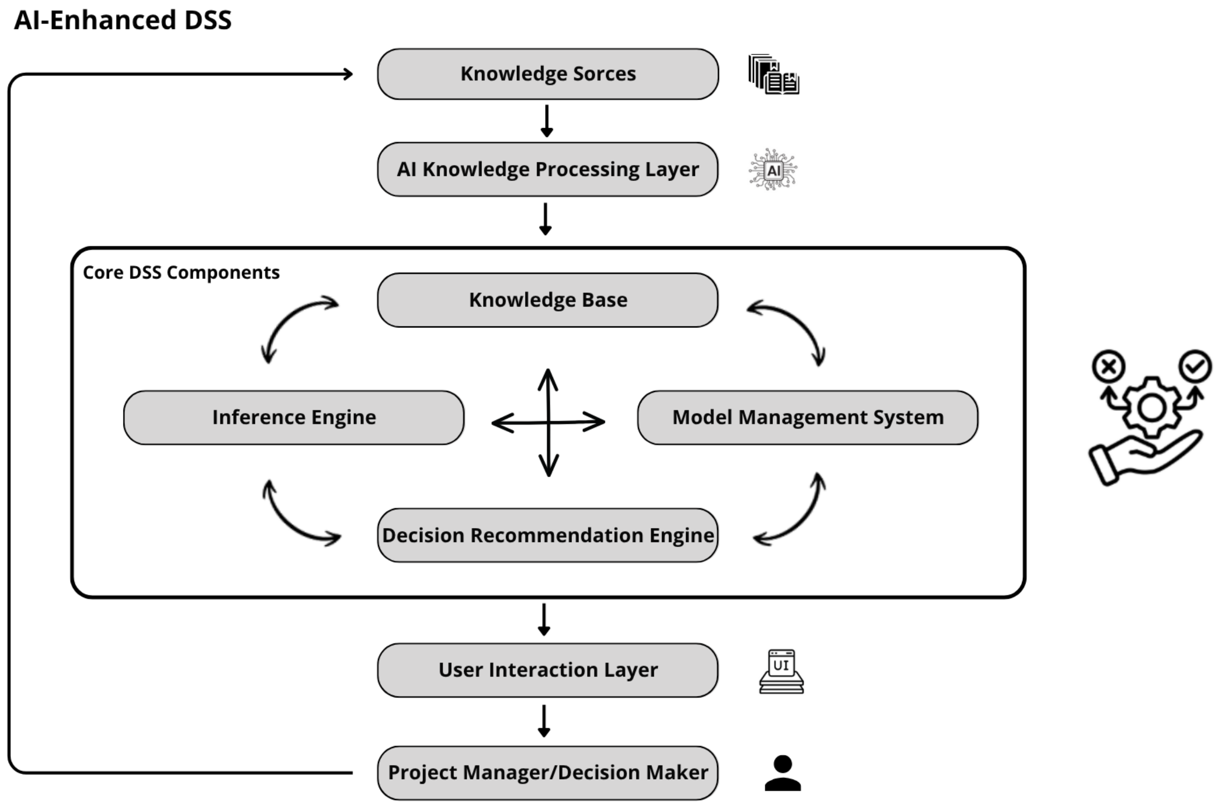

Figure 4.1 - Final AI-Enhanced DSS Framework Architecture

4.2.3 Knowledge Flow and Operational Dynamics

The AI-enhanced DSS framework is designed as an integrated ecosystem that supports continuous, intelligent, and adaptive decision-making within project management contexts. It operates dynamically, leveraging artificial intelligence across multiple interconnected components. The knowledge flow through this architecture involves several distinct but interconnected stages.

This section explains, step by step, how knowledge is captured, processed, stored, and re-applied through the system — transforming fragmented organizational experience into structured, actionable decision support for project managers.

1. Knowledge Acquisition and Integration

Initially, diverse project-related knowledge sources—ranging from structured documents, databases, historical records, emails, and reports to unstructured communications—are systematically gathered. These data streams enter the AI Knowledge Processing Layer, where sophisticated AI techniques such as Natural Language Processing (NLP), Machine Learning (ML), and semantic analytics are utilized. At this stage, raw data is transformed into structured, meaningful, and actionable knowledge, ready for deeper processing and utilization within the system.

"Everything starts with knowledge entering the system — structured or unstructured."

Sources Include:

Project Reports, Meeting Minutes, Risk Logs, Technical Documents, Emails, Chats, Lessons Learned Repositories, External Data (best practices, regulations, market data), etc.

How it Happens:

- Automated data connectors (from PM software, emails, cloud drives)
- Manual upload (contracts, reports)
- AI-powered parsing of unstructured content (NLP for chat, emails, documents)

Purpose:

→ *Capture knowledge naturally where it already exists.*

2. AI Knowledge Processing and Structuring

Within the AI Knowledge Processing Layer, the collected data undergoes rigorous analysis and semantic interpretation. AI algorithms classify, tag, summarize, and derive insights, effectively creating a rich, contextually relevant knowledge foundation. This refined knowledge is then systematically fed into the interconnected Core DSS Components to enable further analysis, reasoning, and predictive modeling.

"This is the smart brain of the system."

AI processes incoming knowledge by:

Summarizing long content (meeting minutes → key points), *Classifying and tagging automatically* (project phase, risk level, topic), *Identifying relationships and building knowledge graphs*, *Cleaning data* (removing duplications, correcting inconsistencies)

AI Techniques Used:

NLP (Natural Language Processing) - Machine Learning Classification - Entity Recognition - Pattern Detection - Semantic Analysis – Other techniques

Purpose:

→ *Transform scattered data into structured, meaningful, ready-to-use knowledge.*

3. Integrated Analysis via Core DSS Components

The Core DSS Components—comprising the Knowledge Base, Model Management System, Inference Engine, and Decision Recommendation Engine—operate interactively and dynamically:

Knowledge Base: Stores and continually updates the refined knowledge, ensuring immediate and relevant data access for all system components. AI-driven algorithms within the Knowledge Base maintain dynamic categorization, indexing, and retrieval efficiency.

Model Management System: Leverages predictive analytics, simulation models, and scenario forecasting tools, using AI-enhanced predictive models trained on historical and real-time knowledge to anticipate potential project outcomes, risks, and opportunities.

Inference Engine: Employs logical reasoning and AI-driven inference to derive deeper insights, identify hidden patterns, validate hypotheses, and interpret knowledge for effective decision-making.

Decision Recommendation Engine: Integrates inputs from the Knowledge Base, Model Management System, and Inference Engine to generate real-time, context-aware recommendations tailored explicitly to the decision-maker's needs, context, and role within the project.

These components maintain continuous, bidirectional information flows, creating a dynamic ecosystem of ongoing knowledge exchange, enrichment, and refinement.

4. User Interaction and Decision-Making

The User Interaction Layer provides an intuitive, accessible interface through which project managers and decision-makers interact with the DSS. Users can query the system, receive real-time recommendations, explore potential outcomes through simulations, and review inferred insights. User interactions and decision feedback are captured, further informing and optimizing future recommendations and system accuracy.

"This is where AI meets real project life."

How the User Works with the System:

- Smart Search Queries: *"Show me risks from similar past projects."*
- Recommendations: *"Based on this situation, consider these actions."*
- Visual Dashboards: KPIs, Resource Maps, Risk Heatmaps
- Chatbot Assistance: FAQ-style AI helpers
- Scenario Simulations: Predictive models based on past patterns

Purpose: → *Support decisions at the moment they happen — without hunting through files.*

5. Continuous Knowledge Feedback Loop

Decisions, user interactions, and outcomes from project implementation are continuously fed back into the Knowledge Base. This continuous learning loop enables the DSS to adapt dynamically, progressively enhancing its accuracy, contextual sensitivity, and predictive reliability, ensuring sustained improvement in decision-making quality over time.

"This is the soul of the system — it evolves."

Every decision, action, and new project adds new knowledge by **Capturing decision outcomes** (*"this worked / this failed"*), **Receiving feedback from users** (*correct, wrong, useful, outdated*), and the **self-improvement of the system over time** (learning from usage patterns).

Purpose: → *The more the system is used → the smarter it becomes.*

4.2.4 Conclusion of Operational Flow

The operational flow of the AI-enhanced DSS is purposefully designed to function not as a static information repository but as a living, learning, decision-support ecosystem.

Its value lies in:

1. Reducing time wasted searching for knowledge
2. Capturing lessons as they happen
3. Making organizational experience continuously available
4. Guiding project managers with actionable insights, not just raw data
5. Creating a true ***Knowledge Memory System*** for project environments

This framework transforms how project knowledge is handled — from passive storage to active support — making decisions faster, smarter, and deeply informed by real organizational learning.

4.3 Practical Use Scenarios in Project Management

4.3.1 Introduction

The true strength and value of any Knowledge Management (KM) system lies not only in its design but in its capacity to address real-world challenges within the organization it serves. In project-based environments — and especially in complex Engineering, Procurement, and Construction (EPC) projects — knowledge flows are often fragmented, dynamic, and difficult to capture or reuse effectively.

This section presents a structured set of practical use cases, demonstrating how the proposed AI-enhanced Decision Support System (DSS) for KM operates within various phases of the EPC project lifecycle, as well as beyond it. The aim is to go beyond abstract technological benefits of AI and focus explicitly on the value generated when AI is purposefully integrated within KM systems to support project managers, engineers, procurement teams, and construction staff.

The scenarios are divided into two main categories:

1. Specific use cases within the EPC project phases

2. Additional organizational use cases beyond EPC boundaries

This structure allows for a comprehensive visualization of the system's operational potential across different knowledge-intensive situations.

4.3.2 Practical Use Cases of AI-Enhanced DSS in the context of EPC

4.3.2.1 Engineering Phase

Use Case 1: Design Optimization

Challenge	***AI-Enhanced DSS Application***	***Benefit***
Traditional design processes often rely on historical data and engineer experience, which may not account for the vast array of variables in complex projects.	Utilizes machine learning algorithms to analyze historical project data, environmental factors, and material properties, generating optimized design alternatives that meet specified criteria.	Improves design efficiency and effectiveness, leading to cost savings and enhanced project outcomes.

Use Case 2: Risk Identification and Mitigation

Challenge	***AI-Enhanced DSS Application***	***Benefit***
Identifying potential risks early in the design phase is critical but challenging due to the complexity of variables involved.	Employs predictive analytics to assess design parameters and historical data, identifying potential risks and suggesting mitigation strategies.	Enhances proactive risk management, reducing the likelihood of costly design changes later in the project.

Use Case 3: Knowledge Management

Challenge	***AI-Enhanced DSS Application***	***Benefit***
Capturing and reusing knowledge from past projects is often inefficient, leading to repeated mistakes and missed opportunities for improvement.	Implements natural language processing to extract insights from previous project documentation, making relevant knowledge easily accessible for current projects.	Facilitates continuous learning and improvement by leveraging organizational knowledge effectively.

4.3.2.2 Procurement Phase

Use Case 4: Supplier Evaluation and Selection

Challenge	***AI-Enhanced DSS Application***	***Benefit***
Assessing supplier performance and reliability can be time-consuming and subjective.	Analyzes historical supplier data, including delivery times, quality metrics, and compliance records, to provide objective evaluations and recommendations.	Facilitates continuous learning and improvement by leveraging organizational knowledge effectively.

Use Case 5: Demand Forecasting

Challenge	***AI-Enhanced DSS Application***	***Benefit***
Accurately predicting material and equipment needs is essential to avoid shortages or excess inventory.	Utilizes forecasting models that consider project schedules, historical consumption patterns, and market trends to predict procurement needs.	Optimizes inventory management, reducing costs associated with overstocking or expedited orders.

Use Case 6: Contract Management

Challenge	***AI-Enhanced DSS Application***	***Benefit***
Managing numerous contracts with varying terms and conditions can be complex and prone to errors.	Applies text analytics to contract documents to identify key clauses, deadlines, and compliance requirements, providing alerts and summaries for contract managers.	Improves contract compliance and reduces legal risks associated with mismanaged agreements.

4.3.2.3 Construction Phase

Use Case 7: Schedule Optimization

Challenge	***AI-Enhanced DSS Application***	***Benefit***
Maintaining project schedules is difficult due to unforeseen delays and resource constraints.	Analyzes real-time project data and external factors (e.g., weather forecasts) to adjust schedules dynamically, suggesting optimal resource allocation.	Enhances schedule adherence and resource utilization, minimizing delays and associated costs.

Use Case 8: Quality Control

Challenge	***AI-Enhanced DSS Application***	***Benefit***
Ensuring construction quality requires continuous monitoring, which can be labor-intensive.	Employs computer vision and sensor data to detect deviations from quality standards in real-time, alerting supervisors to potential issues (Particularly valuable in the context of Industry 4.0 enhanced projects and workplaces).	Improves construction quality and reduces rework by enabling prompt corrective actions.

Use Case 9: Safety Management

Challenge	***AI-Enhanced DSS Application***	***Benefit***
Maintaining a safe construction site is paramount but challenging due to dynamic environments and human factors.	Analyzes data from wearables, cameras, and incident reports to identify safety risks and recommends preventive measures (Industry 4.0 Development).	Enhances worker safety and reduces incidents by proactively addressing potential hazards.

4.3.3 Additional Use Cases Beyond EPC

Use Case 10. Cross-Project Knowledge Transfer & Learning (Portfolio Management)

Problem	***AI-Enhanced DSS Application***	***Value***
Organizations manage multiple projects simultaneously, but valuable knowledge stays trapped inside individual projects.	- Detects similarities between ongoing and past projects automatically. - Suggests relevant documents, lessons learned, and risks based on project profiles.	• Turns isolated project experiences into an organizational asset. • Avoids "reinventing the wheel" every project cycle.

Use Case 11. Stakeholder & Communication Knowledge Management

Problem	***AI-Enhanced DSS Application***	***Value***
Managing complex stakeholder communications, expectations, and histories is difficult over long projects.	- Analyzes historical communication data (emails, minutes, decisions). - Summarizes stakeholder preferences, past conflicts, sensitive topics.	• Supports PMs in stakeholder management strategy. • Preserves negotiation history & lessons in human interactions.

Use Case 12. Change Management & Organizational Memory

Problem	*AI-Enhanced DSS Application*	*Value*
Organizations often face change (mergers, reorgs, team reshuffles) → and lose critical knowledge.	- Captures tacit knowledge from leaving employees through structured interviews auto-transcribed and summarized. - Builds knowledge profiles linked to roles rather than individuals.	• Preserves critical know-how beyond employee turnover. • Eases onboarding and transition phases.

Use Case 13. Real-Time Decision Support in Crisis Management

Problem	*AI-Enhanced DSS Application*	*Value*
Unexpected events (crises, risks realized, urgent escalations) require fast, knowledge-driven decisions.	- Retrieves knowledge from past crisis situations. - Suggests action paths used before. - Offers checklists or decision pathways instantly.	• Reduces chaos in crisis. • Provides calm, evidence-based guidance from organizational history.

Use Case 14. Legal & Regulatory Knowledge Management in Projects

Problem	***AI-Enhanced DSS Application***	***Value***
Complex projects (esp. international) require compliance with many local laws/regulations.	- Stores legal precedents, regulations, country-specific restrictions. - Alerts users when decisions might conflict with regulations. - Suggests documentation patterns used successfully before.	• Reduces compliance risks. • Speeds up regulatory checks.

Use Case 15. Knowledge Gap Analysis & Recommendations

Problem	***AI-Enhanced DSS Application***	***Value***
Organizations don't know what they don't know.	- Analyzes patterns of knowledge access. - Detects under-documented project areas. - Recommends content creation (e.g., missing procedures, FAQs).	• Keeps KM systems healthy and growing. • Encourages content creation where it's missing.

Use Case 16. AI-supported Meeting Knowledge Management

Problem	*AI-Enhanced DSS Application*	*Value*
Meetings generate knowledge → but that knowledge disappears in minutes.	- AI automatically transcribes, tags, summarizes meetings. - Links action points to projects/tasks automatically.	• Turns meetings into permanent, retrievable, structured organizational memory.

4.3.4 Summary

The following two tables provide a structured synthesis of the practical use cases associated with the proposed AI-enhanced DSS framework. The first table organizes the use cases based on their relevance to project lifecycle stages—distinguishing between Engineering, Procurement, and Construction (EPC) phases and broader organizational applications *(Table 4.1)*. The second table presents the same use cases aligned with key Knowledge Management (KM) functionalities, offering a complementary perspective that maps AI interventions to KM processes such as capture, storage, dissemination, application, and learning *(Table 4.2).*

4.3.4.1 Classified for EPC or Organizational

Table 4.1 - Summary and classification of practical use cases for AI-enhanced DSS in project management. Use cases are organized by project phase and application area (EPC and Organizational Use Cases), with corresponding AI capabilities and resulting benefits outlined.

Category	Phase/Application Area	Use Case	AI-Enhanced DSS Capabilities	Primary Benefit
EPC Project Phases	**Engineering**	**Design Optimization**	ML-driven design alternatives based on historical data and environmental factors.	Efficient, cost-effective, optimized project designs.

	Engineering	**Risk Identification & Mitigation**	Predictive analytics identifying risks early in design phase.	Proactive risk management and cost reduction.
	Engineering	**Knowledge Management**	NLP extraction and categorization from historical project documentation.	Effective reuse of organizational knowledge.
	Procurement	**Supplier Evaluation & Selection**	Historical supplier data analysis and objective supplier recommendations.	Reliable procurement and reduced project delays.
	Procurement	**Demand Forecasting**	Predictive models analyzing historical consumption and project schedules.	Optimized inventory management, cost reduction.
	Procurement	**Contract Management**	Text analytics summarizing key clauses, deadlines, and compliance requirements.	Enhanced contract compliance and reduced legal risk.
	Construction	**Schedule Optimization**	Real-time analytics adjusting schedules dynamically based on project data and external conditions.	Minimized project delays, optimal resource allocation.
	Construction	**Quality Control**	Real-time quality monitoring using computer vision and sensor analytics (Industry 4.0).	Enhanced quality standards and reduced rework.
	Construction	**Safety Management**	Analysis of wearables, sensor data, and incident reports for safety risk identification.	Improved workplace safety and incident reduction.
Beyond EPC (Organizational)	**Portfolio Management**	**Cross-Project Knowledge Transfer & Learning**	Automated similarity detection between projects and recommendations of lessons learned.	Improved knowledge reuse and organizational learning.

	Stakeholder Management	**Stakeholder & Communication Knowledge Management**	NLP summarization of stakeholder interactions and historical communication data.	Enhanced stakeholder strategy and preserved negotiation knowledge.
	Change Management	**Change Management & Organizational Memory**	Tacit knowledge capture via structured, auto-transcribed interviews and knowledge profiling.	Preservation of critical knowledge during organizational changes.
	Crisis Management	**Real-Time Decision Support in Crisis Management**	Instant retrieval of historical crisis-handling knowledge and decision pathways.	Effective, evidence-based crisis management decisions.
	Regulatory Compliance	**Legal & Regulatory Knowledge Management**	Regulatory compliance monitoring and alerts based on historical legal documentation.	Reduced compliance risk and faster regulatory checks.
	Content Management & KM Health	**Knowledge Gap Analysis & Recommendations**	Analysis of KM system usage patterns and automated recommendation for content creation.	Improved completeness and quality of organizational knowledge.
	Meeting Management	**AI-supported Meeting Knowledge Management**	Automated transcription, tagging, and summarization of meeting knowledge.	Permanent, structured, retrievable meeting knowledge.

Note:

This table summarizes and classifies practical AI-Enhanced DSS use cases, highlighting their context, AI capabilities applied, and primary benefits realized within project management and beyond. It demonstrates the extensive value generated when AI integration specifically targets real-world KM and PM challenges.

4.3.4.2 Classified for Knowledge Management Phases

Table 4.2 - Integrated summary of AI-enhanced DSS use cases aligned with Knowledge Management (KM) phases. This table illustrates how AI technologies contribute to knowledge capture, organization, retrieval, application, and continuous improvement in project-based contexts.

KM Phase	Project Phase/Context	Use Case	AI-Enhanced DSS Application	Primary Benefit
Knowledge Capture & Creation	**Engineering**	**Expert tacit knowledge capture and design optimization**	NLP and ML analyzing historical data, expert interactions, and project documentation	Optimized design, captured expert knowledge
	Meetings & Interviews	**Auto-transcribing meetings and interviews**	AI-driven transcription, summarization, and tagging of meetings/interviews	Preserved and structured meeting knowledge
	Change Management	**Organizational memory capture during transitions**	Structured, automated capture of tacit knowledge from departing employees	Critical know-how retained during turnover
Knowledge Organization & Storage	**Procurement**	**Centralized and organized supplier records**	AI-driven categorization and evaluation of historical supplier performance data	Improved supplier selection and reduced delays
	Regulatory Compliance	**Legal & regulatory knowledge repository**	AI-supported classification and storage of regulations, contracts, and legal precedents	Enhanced compliance and risk management
Knowledge Retrieval & Dissemination	**Engineering**	**Real-time retrieval of design documents**	Context-aware semantic search and knowledge recommendation system	Efficient design decision-making
	Portfolio Management	**Cross-project knowledge recommendations**	Automated similarity detection and retrieval of relevant project documents and lessons	Enhanced reuse of project knowledge
	Stakeholder Management	**Stakeholder communication insights**	NLP-driven analysis of communication history and stakeholder interactions	Improved stakeholder relationship management

Knowledge Application	**Construction**	**Real-time site risk response**	Predictive analytics for dynamic schedule optimization and risk mitigation strategies	Minimized project delays and enhanced safety
	Crisis Management	**Real-time decision support in crisis scenarios**	AI-driven retrieval of historical crisis resolutions, recommending immediate action paths	Swift, informed crisis response
	Procurement	**Demand forecasting and contract management**	Predictive analytics forecasting procurement needs and automated contract compliance checks	Optimized inventory and reduced legal risks
Knowledge Learning & Improvement	**Procurement**	**Procurement lessons learned**	NLP and ML-based analysis of procurement history to derive actionable insights	Continuous improvement of procurement strategies
	Construction	**Quality control and safety management**	AI-powered computer vision and analytics for quality and safety monitoring (Industry 4.0)	Enhanced quality standards, reduced incidents
	KM System Health	**Knowledge gap analysis and content recommendations**	AI-based usage pattern analysis identifying knowledge gaps and suggesting content creation	Improved completeness and quality of KM system

Note:
This table integrates AI-Enhanced DSS practical use cases with established KM phases, clearly illustrating how each phase is effectively enhanced by AI-driven methods. It succinctly captures how AI integration systematically addresses both project-specific and broader organizational knowledge management challenges, delivering significant operational benefits and supporting continuous improvement.

4.3.4.3 Conclusion

This set of use cases clearly demonstrates that the value of an AI-enhanced KM DSS extends far beyond storing information *(Figure 4.2)*. It actively transforms knowledge from static documents into living, context-aware, accessible resources that support real-world project decisions.

In EPC project environments, this translates to faster knowledge retrieval, more accurate decisions, stronger organizational memory, reduced knowledge loss, proactive risk management, and embedded continuous learning culture. Moreover, in broader organizational settings, the framework becomes a powerful corporate knowledge infrastructure, capable of preserving strategic knowledge, supporting crisis management, improving stakeholder engagement, and enhancing project delivery performance at multiple levels.

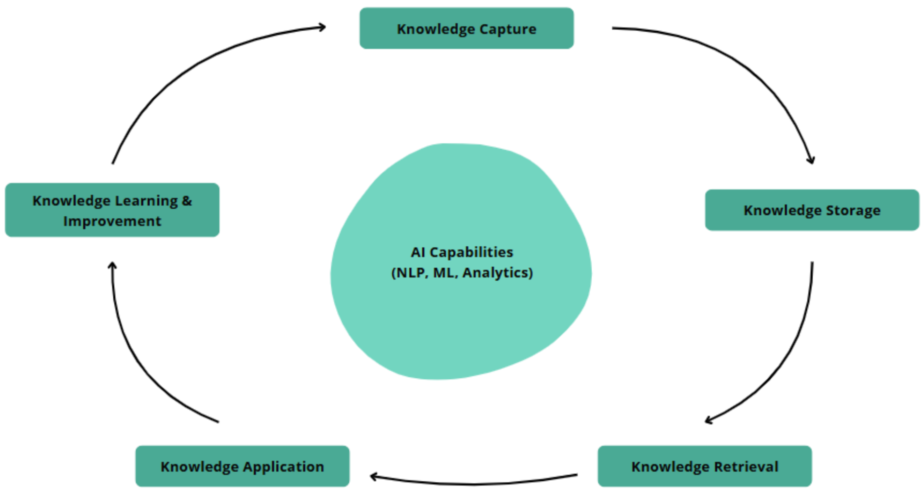

Figure 4.2 - This diagram visually represents the continuous knowledge management lifecycle as supported by the proposed AI-enhanced DSS framework. AI capabilities (Natural Language Processing, Machine Learning, Analytics) operate at the center of the cycle, enhancing each phase — from knowledge capture to storage, retrieval, application, and continuous learning — thereby transforming organizational knowledge from a static resource into a dynamic strategic asset.

In the following section, a critical reflection will examine in detail the theoretical and practical value this framework brings to project management and KM disciplines.

4.4 Critical Reflection on the Framework's Value

4.4.1 Introduction

A framework, in isolation, holds little value unless it responds effectively to the real-world challenges it claims to address. This section presents a critical reflection on the AI-enhanced Knowledge Management Decision Support System framework proposed in this thesis, not merely in terms of its technical design, but more importantly, in its strategic relevance, practical utility, and unique contribution to modern project management environments.

The reflection is structured around two key dimensions:

1. *Theoretical Contribution*: Positioning within academic knowledge of KM, DSS, AI, and PM.
2. *Practical Contribution*: Operational and strategic value for organizations managing complex projects, particularly in EPC contexts.

4.4.2 Theoretical Contribution

a. Bridging a Rarely Connected Gap: AI × KM × DSS × Project Management

Although there is extensive scholarly work on Artificial Intelligence (AI), Knowledge Management (KM), and Decision Support Systems (DSS) as individual domains, their integrated application within the specific context of project management remains notably underexplored. This framework fills this precise gap by:

- Positioning AI not as a parallel tool, but as an *embedded processor* within KM flows.
- Not treating DSS as static dashboards, but as *adaptive knowledge-driven environments*.
- Making KM operational within projects — where knowledge is dynamic, contextual, and often tacit or undocumented.

b. Moving from Passive KM to Active Knowledge Engagement

Most KM systems in project settings remain repositories — focused on storage and retrieval.

This framework transforms that paradigm by:

- Enabling real-time learning from data streams.
- Promoting contextualized recommendations, not just information access.
- Turning project KM from a passive archive to an active decision participant.

c. Reinforcing KM as a Competitive Project Asset

Traditional literature positions KM as a strategic asset mostly at organizational levels.

This thesis shows that:

- KM is equally critical *inside* projects.
- The real bottleneck is not data absence — it is knowledge *accessibility at the moment of decision-making*.
- AI-enhanced DSS becomes a *<u>scalable organizational brain</u>*, preserving project knowledge beyond people and time boundaries.

4.4.3 Practical Contribution

a. Direct Response to PM's Most Painful Knowledge Challenges

The following table illustrates how the proposed AI-enhanced DSS framework directly addresses some of the most pressing knowledge management challenges faced by project managers in practice.

Table 4.3 - Mapping of common project management knowledge challenges to the specific responses provided by the AI-enhanced DSS framework.

PM Knowledge Challenge	Framework Response
Knowledge fragmentation across teams & tools	Unified knowledge assets integration layer
Difficulty retrieving relevant past experience	AI-powered search, summarization, and recommendations
Tacit knowledge loss due to staff turnover	Structured expert knowledge capturing process
Slow decisions in time-pressured environments	Real-time, context-aware decision support outputs
Poor lessons learned transfer between projects	Cross-project learning & knowledge transfer module
Documentation overload without synthesis	Automated knowledge processing & summaries

b. Enabling a True Corporate Memory System

Most organizations accept knowledge loss in projects as "normal." This framework challenges that prevailing assumption by demonstrating how an AI-enabled Decision Support System (DSS) can function as **a dynamic, living repository of organizational memory**. Through continuous learning and intelligent integration, the system ensures that critical knowledge becomes embedded within institutional processes—detached from reliance on any single individual. As such, accumulated experience is no longer lost but instead preserved, structured, and transformed into a navigable and evolving strategic asset.

- AI-enabled DSS can evolve into a *living organizational memory*.
- Knowledge can become *independent* from specific individuals.
- Experience is no longer lost but becomes a navigable, evolving strategic asset.

c. Embedding AI into Everyday Project Life — Not as a Disruption, but as an Invisible Ally

AI here is not a futuristic layer reserved for data scientists — but a silent assistant integrated into daily workflows. Suitable to be used for various objectives such as: Assisting in meetings (auto-minutes), Helping procurement (supplier knowledge profiles), Supporting engineers (design knowledge retrieval), Enhancing construction teams (real-time safety knowledge), Supporting PMs in crises (decision pathways from history), etc.

d. Adaptability Across Industries and Organizational Sizes

While originally developed with EPC projects in mind, the framework is modular and highly adaptable. It can be scaled up or down to suit the needs of agile teams, complex program environments, or even cross-organizational collaborations. Furthermore, its structure allows it to function as a flexible knowledge infrastructure, making it applicable across a variety of project domains.

4.4.4 Reflections on Limitations & Real-World Implementation Challenges

Being critically honest:

- The framework is conceptual and requires adaptation based on organizational maturity.
- AI's success heavily depends on data quality and system adoption by users.
- There are ethical considerations around privacy, AI transparency, and human oversight.
- Initial investments in structuring knowledge assets and setting up AI tools can be an issue.

However, the long-term strategic payoff — in knowledge retention, decision-making speed, and organizational learning — far outweighs these early challenges.

4.4.5 Final Thought

This thesis has attempted to do more than design a theoretical framework. It has presented a vision, grounded in project management realities, of how organizations can transition from treating knowledge as a static commodity into cultivating a dynamic, AI-powered knowledge environment that genuinely supports the most human of all activities: ***deciding wisely, under pressure, in uncertainty, with experience at hand.***

This is not just about AI. It is about *Knowledge Intelligence* becoming a natural part of everyday project management life and to optimize the use of data and resources we have already available.

4.5 Chapter Summary

Chapter 4 has represented a crucial turning point in this thesis, transitioning from the conceptual development of the AI-enhanced Knowledge Management Decision Support System (KM DSS) presented in Chapter 3 to its operationalization and real-world applicability within project management environments. While the previous chapters focused on diagnosing existing limitations of Knowledge Management (KM) in project contexts and proposing a structured framework to address them, Chapter 4 has been dedicated to demonstrating how this framework actually *works*, *lives*, and *creates value* within the dynamics of projects, particularly those in Engineering, Procurement, and Construction (EPC) settings.

4.5.1 Key Accomplishments of Chapter 4

The table below summarizes the key accomplishments of Chapter 4, linking each major section to its intended contribution and the results achieved through its implementation.

Table 4.4 - Overview of Chapter 4 accomplishments, detailing the framework presentation, use case applications, and critical reflection on theoretical and practical impact.

Section	**Contribution**	**Result Achieved**
4.2 Final Framework Presentation	Clarified and visualized the architecture of the AI-enhanced KM DSS and its Operational Flow	Provided a clear model with defined components and their roles in KM processes and demonstrated how knowledge is captured, processed, stored, and re-used to support decisions in real time
4.3 Practical Use Scenarios	Applied the framework across real-life project phases	Provided concrete, relatable use cases within Engineering, Procurement, Construction, and beyond — proving adaptability and strategic fit
4.4 Critical Reflection	Positioned the framework's theoretical and practical uniqueness	Strongly justified why this framework adds value compared to existing KM or DSS approaches — making it deeply relevant and operational

4.5.2 Main Insights Gained

→ The AI-enhanced DSS proposed in this thesis is not merely a technological upgrade but a strategic response to deeply-rooted knowledge management deficiencies in project-based environments.

→ Its operational logic revolves around:

- Capturing knowledge not when convenient — but when it happens.
- Processing knowledge not to store — but to support real decisions.
- Reusing knowledge not when manually retrieved — but when needed automatically.

4.5.3 Recurrent Value Themes Demonstrated in Chapter 4

The table below captures the key value themes emphasized throughout Chapter 4, illustrating how the AI-enhanced DSS framework operationalizes them across project management contexts.

Table 4.5 - Recurrent value themes and their practical manifestations within the AI-enhanced KM DSS framework.

VALUE THEME	MANIFESTATION IN THE FRAMEWORK
KNOWLEDGE AS A DYNAMIC ASSET	Continuous learning and feedback loops built-in the DSS
AI AS A SUPPORTIVE ENABLER	Invisible assistant embedded in PM daily workflows
REDUCTION OF KNOWLEDGE FRAGMENTATION	Unified integration of knowledge sources and smart processing
OPERATIONAL SPEED & DECISION CONFIDENCE	Real-time access to context-aware, relevant knowledge assets
ORGANIZATIONAL MEMORY PRESERVATION	Capturing tacit knowledge systematically and making it retrievable

This chapter transforms the framework from “*A theoretical architecture*” into “*A practical, organizational guide for rethinking how knowledge is captured, flows, and drives decisions inside projects*”.

It demonstrates that the true contribution of AI in KM is not about automation alone, but about enriching human decision-making with structured, timely, and meaningful knowledge access.

5. Conclusion and Discussion

5.1 Recap of the Thesis Journey

5.1.1 Introduction

This thesis began with a simple yet profound realization: that in today's complex, fast-paced project environments, knowledge is both an organization's greatest asset and, paradoxically, one of its most underutilized. The persistent loss of experience, the fragmentation of information, and the growing difficulty of making timely, well-informed decisions pointed to a clear research gap. Traditional knowledge management (KM) systems, while essential, were not keeping pace with the scale, speed, and complexity of modern project delivery.

At the same time, the rise of Artificial Intelligence (AI) offered powerful new capabilities to interpret, contextualize, and activate knowledge in ways that human-centered systems alone could not. However, while AI tools had been explored in various organizational functions, their potential to empower KM specifically — and to do so within a Decision Support System (DSS) architecture tailored for project environments — remained largely untapped.

5.1.2 Research Problem and Aim

This thesis set out to bridge this gap by asking a central question:

How can AI be integrated into a DSS to enhance knowledge management and decision-making in project-based environments?

The aim of this research was not to develop another technical AI solution, nor to engage in a comparative analysis of AI models. Rather, it focused on designing a strategic and operationally viable AI-enhanced Knowledge Management Decision Support System (KM DSS). The framework is intended to preserve and activate organizational historical knowledge, support real-time and context-aware decision-making, enhance KM workflows across the entire project lifecycle, and ultimately deliver actionable value to managers, engineers, and project teams operating under pressure.

5.1.3 Research Approach and Method

To achieve this aim, the research adopted a **design science methodology** — appropriate for problems where no pre-existing solution exists and where the desired outcome is a practical, innovative artefact.

Chapter 2 offered an extensive literature review, identifying both the theoretical foundations and the critical gaps across KM, DSS, and AI domains.

Chapter 3 designed the core framework, grounded in Holsapple & Whinston's DSS model, and modified it to incorporate AI functionalities across KM phases.

Chapter 4 operationalized the framework through detailed scenarios and use cases — particularly within EPC environments — and critically evaluated its potential impact.

5.1.4 Key Milestones and Achievements

This thesis delivered the following:

- A clear articulation of KM's central role in project management and its limitations in current practice
- A rigorous conceptual framework for an **AI-enhanced DSS for KM**
- Operational diagrams illustrating how knowledge flows through the system
- Use case modeling across the entire EPC lifecycle — and beyond
- A deep critical reflection showing both theoretical and practical contributions

5.1.5 Transition to the Next Sections

The rest of this chapter will now build on this foundation to **examine the thesis' theoretical and practical contributions**, acknowledge **limitations** with transparency, suggest directions for **future research and development**, and offer **final thoughts**—framing this work not just as an academic contribution, but as a roadmap for future-ready, knowledge-driven project management systems.

5.2 Theoretical Contributions

5.2.1 Introduction

Every thesis, to claim its place in academic literature, must go beyond summarizing existing knowledge. It must position itself within existing theories and frameworks while contributing something new, refined, or expanded.

This section reflects on the theoretical contributions of this research, particularly in relation to four critical bodies of knowledge:

- Knowledge Management (KM)
- Decision Support Systems (DSS)
- Artificial Intelligence (AI) integration in organizations
- Project Management (PM) knowledge practices

5.2.2 Contribution to Knowledge Management (KM) Theory

Historically, much of the knowledge management literature has concentrated on foundational elements such as knowledge capture, storage, retrieval, and the distinction between tacit and explicit knowledge.

However, this thesis advances KM theory by reframing knowledge not simply as a stored asset, but as an active and evolving component of decision-making processes. It illustrates how AI technologies can bring KM principles to life in dynamic, real-time contexts rather than treating them as static systems. The thesis also extends the role of KM from a background organizational function to a central enabler of decision-making, particularly within project-based environments. Furthermore, it bridges traditional KM approaches with real-time knowledge flow models, enhancing organizational responsiveness in fast-changing and complex settings.

5.2.3 Contribution to Decision Support Systems (DSS) Theory

Traditional DSS theory (Sprague, Holsapple & Whinston, Power) provided the foundations for decision support architecture. This thesis contributes by:

Evolving DSS design to accommodate AI-driven knowledge processing layers.

- ➢ A feature largely missing from classical DSS models.

Integrating KM processes *within* DSS architecture.

- ➢ Rather than treating KM and DSS as separate systems.

Positioning DSS not just as data-driven environments, but as *knowledge-driven environments*.

- ➢ Emphasizing organizational learning and knowledge reuse.

5.2.4 Contribution to AI Integration Literature

Much of the existing literature on AI integration in organizations tends to be tool-specific, focusing on applications such as AI for marketing, HR, or analytics. It often remains functionally isolated and primarily emphasizes automation, rather than exploring how AI can enable and enhance organizational knowledge.

- Tool-specific
- Functionally isolated
- Focused on automation

This thesis advances the theory of AI integration by treating AI not simply as a tool, but as a processor of organizational knowledge. It outlines AI functionalities across the full knowledge management lifecycle, including knowledge capture, storage, retrieval, application, and continuous learning. In addition, it proposes a human-centric approach in which AI supports and strengthens human judgment, rather than replacing it, especially in decision-making situations marked by uncertainty, which are common in project management.

- Treating AI as an *organizational knowledge processor*.
- Structuring AI functionalities across the entire KM lifecycle
- Proposing a human-centric AI approach where AI empowers human judgment

5.2.5 Contribution to Project Management (PM) Knowledge Practices

Project management literature often treats **knowledge management** and **decision-making** as distinct domains. knowledge processes are typically confined to lessons learned sessions or document repositories, while decision-making relies on tools, dashboards, and planning models.

This thesis challenges that separation by integrating AI-enhanced knowledge management directly into the core of project management decision-making workflows. It demonstrates how AI-powered KM decision support systems can address common challenges in project environments, such as knowledge fragmentation, loss of experiential insights, and slow access to relevant information. The proposed framework is designed to adapt to the dynamic, uncertain, and multi-actor nature of real-world projects, positioning knowledge as a continuous, embedded driver of better decisions.

5.2.6 A Cross-Disciplinary Contribution

Finally, this thesis contributes to the ongoing evolution of management engineering research by:

- Bridging information systems, organizational knowledge theory, artificial intelligence, and project management into a single, coherent framework.

- Demonstrating the feasibility of designing knowledge ecosystems that are not only technologically advanced but also deeply aligned with human workflows and organizational realities.

5.2.7 Summary

The theoretical contributions of this thesis lie in its capacity to reframe how knowledge management is understood and operationalized within project environments — by embedding AI directly within the processes that capture, structure, and apply knowledge to support human decision-making.

This research offers a significant evolution of both KM and DSS theory, providing a model for future studies and organizational practices seeking to integrate AI capabilities into complex, knowledge-intensive project environments.

5.3 Practical Contributions

5.3.1 Introduction

While the theoretical contributions of this thesis position it within academic discussions of KM, DSS, AI, and PM, its true strategic value lies in its practical applicability.

This was never intended to be a purely conceptual or technical exercise detached from reality. From its inception, this research was guided by a pragmatic vision:

To design an AI-enhanced Knowledge Management Decision Support System (KM DSS) capable of genuinely improving how project-based organizations capture, structure, retrieve, and apply knowledge to support better, faster, and smarter decision-making.

This section reflects on the key practical contributions of the research for real-world project management environments, highlighting specific areas where the proposed framework adds operational value.

5.3.2 Transforming Knowledge from Passive Storage to Active Decision Power

Traditional KM systems function largely as document repositories or databases. Their utility depends heavily on users knowing: *What they are looking for? Where it is stored? and How to search for it effectively?*

This thesis contributes a **paradigm shift**:

- Knowledge becomes dynamic, contextual, and accessible exactly when and where decision-makers need it.
- The system proactively assists users rather than waiting for users to initiate a search.
- Project knowledge becomes a *strategic decision enabler* rather than a static archive.

This transformation radically changes how project managers, engineers, procurement officers, and site teams interact with organizational knowledge.

5.3.2 Supporting Critical Decision-Making in Time-Pressured Project Environments

Projects are characterized by: Tight deadlines, High uncertainty, Complex stakeholder networks, and Distributed teams. The proposed AI-enhanced Knowledge Management contributes practically by:

- Enabling real-time access to relevant past knowledge, decisions, risks, and lessons learned.
- Offering personalized knowledge recommendations based on role, project context, and specific queries.
- Helping project teams make informed decisions faster, reducing delays and errors caused by knowledge fragmentation or inaccessibility.

5.3.4 Improving Organizational Memory and Reducing Knowledge Loss

Knowledge loss is one of the most expensive, yet underestimated, challenges in project-based organizations — especially when experts retire or leave, project teams disband, or the lessons learned are poorly documented.

This framework provides a structured knowledge capturing processes, even for tacit knowledge, AI-driven synthesis of dispersed information and the automatic generation of lessons learned from project data.

Outcome: *Organizational memory becomes sustainable, dynamic, and independent of individual people.*

5.3.5 Enhancing Cross-Project Learning and Knowledge Transfer

Often, even within the same organization, projects operate in silos. Lessons learned are not effectively transferred across projects.

Practical contribution of this framework:

- Automatic identification of similar past projects.
- Retrieval of relevant risks, solutions, and expert insights.
- Enabling project managers to avoid reinventing the wheel.

This feature is particularly impactful in large EPC firms or PMOs managing multiple concurrent projects.

5.3.6 Facilitating Better Supplier and Contract Knowledge Management

Procurement and contract management are knowledge-intensive domains often managed by intuition and experience rather than structured knowledge systems.

Contribution of this framework:

- Building supplier knowledge profiles based on performance data.
- AI-supported contract clause identification and risk flagging.
- Supporting procurement decisions with evidence-based insights.

5.3.7 Supporting Safety, Quality, and Compliance through Knowledge Intelligence

Beyond administrative or design knowledge, the system also supports operational excellence:

Table 5.1 - Contributions of the AI-enhanced DSS to safety, quality, and compliance through intelligent knowledge integration.

Domain	Contribution
Safety	Disseminating real-time, context-aware safety knowledge based on past incidents and site conditions.
Quality	Recommending corrective actions based on similar past quality issues.
Compliance	Linking project decisions to regulatory and legal knowledge assets automatically.

5.3.8 Improving Onboarding and Knowledge Access for New Team Members

New team members often spend weeks or even months trying to catch up on critical project knowledge. This framework significantly reduces that onboarding time by providing AI-curated knowledge packs that summarize essential project history, highlight key risks and stakeholders, and consolidate important lessons learned. As a result, onboarding becomes faster, more efficient, and less reliant on informal or ad hoc knowledge transfer.

5.3.9 Usability: Seamless Integration into PM Daily Workflows

Perhaps the most important practical contribution of this framework is its ability to integrate naturally with existing project management tools and platforms. It is designed to be role-aware, delivering tailored insights for engineers, project managers, procurement teams, or safety officers. Crucially, it supports knowledge management not as an additional burden, but as a seamless, almost invisible assistant embedded within the daily workflow of project environments.

5.3.10 Versatility Across Industries and Project Types

While EPC projects served as the primary context for use case modeling, the framework is also applicable across a wide range of industries, including IT, healthcare, construction, infrastructure, and service-oriented projects. It is flexible enough to adapt to organizations of various sizes and different levels of knowledge management maturity. With its modular architecture, the framework allows for incremental implementation, enabling organizations to begin by addressing their most critical knowledge challenges and gradually expand its application over time.

Summary of Practical Contributions

This thesis delivers a framework that:

- Reimagines knowledge management as a live, operational engine of project performance.
- Brings AI not just to data analytics, but to the heart of organizational knowledge flows.
- Provides a scalable, adaptable roadmap for project-driven organizations seeking to reduce knowledge loss, enhance decision quality, and strengthen organizational learning.

It is, ultimately, a framework designed *not only to store what an organization knows — but to ensure that it can use that knowledge better, faster, and smarter.*

5.4 Limitations of the Study

5.4.1 Introduction

While this thesis presents a comprehensive and practical framework for an AI-enhanced Knowledge Management Decision Support System in project-based environments, it is important to acknowledge its limitations. These limitations are not shortcomings, but natural boundaries of a design-oriented, conceptual research endeavor.

This section outlines the scope-related, methodological, technological, and practical constraints that frame the conclusions of this study and inform the basis for future research.

5.4.2 Conceptual Nature of the Research

The most significant limitation of this study lies in its **conceptual design** nature. The framework developed in this thesis has **not yet been empirically implemented or tested** within a live organizational context. Although the use cases are grounded in realistic scenarios and aligned with established project management practices, they remain **hypothetical illustrations**. Furthermore, no user testing, system validation, or empirical performance data was collected. As a result, while the design is robust and theoretically sound, ***its practical effectiveness and the dynamics of organizational adoption still need to be evaluated in real-world settings.***

5.4.3 Dependency on Data and Infrastructure Readiness

AI-driven knowledge management systems rely on several foundational requirements to function effectively. First and foremost, they need high-quality, well-structured organizational data to generate meaningful insights. Seamless integration across multiple tools and platforms is also essential to ensure consistent access to information and reduce fragmentation. In addition, sufficient IT infrastructure must be in place to support the computational demands of AI technologies. Finally, a certain level of organizational digital maturity is necessary to adopt, sustain, and scale these systems successfully.

In practice:

- Many organizations — especially in traditional industries — may **lack the digital ecosystems** needed to fully support the proposed framework.
- AI's ability to provide value depends heavily on the **availability and cleanliness of historical knowledge assets**, which are often fragmented or undocumented.

This may **limit the immediate applicability** of the framework in certain contexts without preliminary investments in KM foundations.

5.4.4 User Adoption and Change Management Challenges

A system like this, while technologically promising, does not exist in a vacuum. **Cultural resistance to AI** and new knowledge management practices can pose significant challenges to user adoption. Successfully implementing such a framework would require not only technical deployment but also comprehensive **training, ongoing support, and robust organizational change management** (elements that were not explored in depth within the scope of this thesis.) Moreover, the framework assumes that users are both **willing and able to engage with AI-supported KM interfaces**, an assumption that may not always hold true in practice. These behavioral and organizational factors are critical to the system's success, yet they lie beyond the primary focus of this design-oriented research.

5.4.5 Ethical and Governance Considerations

Although not a central focus of this thesis, deploying AI-enhanced KM systems raises important ethical questions:

- **Data privacy** and security, especially when integrating sensitive knowledge sources
- **Transparency and explainability** of AI-generated recommendations
- **Bias in AI models** potentially affecting knowledge interpretation or decision pathways

These considerations merit in-depth exploration in follow-up studies, especially if this framework is to be implemented in contexts involving sensitive data or complex stakeholder environments.

5.4.6 Scope-Specific Focus on EPC Context

While the framework is **designed to be modular and adaptable**, the use case modeling and scenarios were constructed with a focus on **Engineering, Procurement, and Construction (EPC)** project environments. This:

- Strengthens relevance in that domain
- But **limits the specificity** of insights for other domains (e.g., healthcare, software development, public administration), unless adapted.

Cross-industry transferability will require **additional contextualization** and validation in future applications.

5.4.7 Summary

The limitations of this thesis do not diminish its value. Rather, they clarify the boundaries of its current contribution and provide a roadmap for further research and development. In summary, the proposed framework:

- Is a **conceptual design**, not yet tested empirically
- Requires **organizational readiness** in terms of data, infrastructure, and culture
- Faces **ethical, behavioral, and contextual challenges** in implementation
- Was modeled primarily for **EPC project environments**, though it is adaptable

These limitations are important considerations for both scholars and practitioners who may wish to build on, extend, or implement this work in the future.

5.5 Recommendations for Future Research

5.5.1 Introduction

This section outlines potential avenues for future research and development, based on the findings, design choices, and limitations discussed throughout this thesis. The proposed AI-enhanced Knowledge Management Decision Support System represents an important conceptual advancement — but its true potential lies in further validation, adaptation, and evolution within diverse organizational settings.

The following research recommendations are structured around five key dimensions:

1. Empirical Validation
2. User Experience and Adoption Studies
3. Technological and System Development Research
4. Ethical, Governance, and AI Transparency Studies
5. Cross-Industry and Cross-Project Adaptations

5.5.2 Empirical Validation and Real-World Implementation

Future research should focus on transforming this conceptual framework into working prototypes and testing them in real project environments.

Recommended approaches:

- Case studies within EPC organizations implementing AI-supported KM practices.
- Pilot implementations of specific modules (e.g., AI-powered knowledge search engine, automatic lessons learned generation).
- Action research with project managers interacting with early versions of the system.
- Measuring impacts on: Decision-making speed, Knowledge reuse frequency, Error reduction, and User satisfaction.

Empirical evidence would significantly strengthen the framework's credibility and practicality.

5.5.3 User Experience (UX) and Adoption Dynamics

Future work should investigate:

- User expectations, preferences, and resistance factors when interacting with AI-enhanced KM tools.
- Optimal interface design for diverse roles (engineers, PMs, procurement officers, executives).
- Factors affecting trust in AI-generated knowledge suggestions.
- Behavioral barriers in knowledge sharing and AI adoption.

Qualitative research methods (interviews, ethnographic studies) and UX testing could provide valuable insights here.

5.5.4 Technological Expansion and AI System Development

Potential research directions include:

- Developing advanced AI modules specialized for KM processes (e.g., AI that distinguishes between critical knowledge vs noise).
- Enhancing knowledge graphs for cross-project learning and intelligent knowledge linking.
- Exploring integrations with existing PM software ecosystems (e.g., Microsoft Project, Primavera, Jira, SAP).
- Investigating system scalability challenges for large, complex multi-project environments.

Technical research could lead to new tools, plugins, or SaaS solutions inspired by this framework.

5.5.5 Ethical, Legal, and Governance Implications

Future studies should delve into the development of ethical frameworks that guide the use of AI-supported knowledge management in organizations. This includes establishing clear guidelines around privacy, transparency, and the degree of user control over AI-driven knowledge recommendations. In parallel, there is a need for thorough risk analyses addressing potential algorithmic bias and its impact on organizational knowledge flows. Equally important is the exploration of governance models that define the boundaries and protocols of AI-human collaboration in decision-making processes. Interdisciplinary research that brings together KM, AI ethics, and organizational theory will be particularly valuable in shaping responsible and effective adoption strategies.

5.5.6 Cross-Industry and Cross-Project Adaptations

While this thesis is focused on EPC projects, future research should test and adapt the framework in other sectors, including: IT and software development, Healthcare project environments, R&D and innovation projects, Construction, manufacturing, consulting, and public sector PMOs, etc. Comparative studies across industries could identify:

- Universal KM DSS principles
- Sector-specific adaptations needed
- Variations in KM maturity and AI readiness

5.5.7 Exploring the Future Role of AI in Organizational Learning Ecosystems

Longer-term research could explore:

- How AI-enhanced KM DSS can become part of broader organizational learning ecosystems.
- The role of AI in knowledge culture transformation.
- Future models where AI supports not just KM but also skill development, coaching, and collaborative intelligence.

This could lead to connecting this thesis to emerging fields like *Organizational Learning 4.0* or *AI-enabled Knowledge Ecosystems*.

5.5.8 Summary

Future research on AI-enhanced KM DSS is not only necessary but offers exciting opportunities across technical, behavioral, ethical, and strategic dimensions.

By moving from design to application, from framework to fieldwork, and from concepts to living systems, future studies can further validate, refine, and expand the vision laid out in this thesis — building organizations where knowledge is no longer static, isolated, or lost, but continuously alive, accessible, and operationally impactful.

5.6 Practical Guidelines for Organizations to Prepare for AI-Enhanced KM DSS Adoption

5.6.1 Introduction

While the proposed AI-enhanced KM DSS framework provides the structure and technological pathways for smarter knowledge-driven decision-making, its successful implementation depends not only on system design but also on organizational readiness. This section offers a set of practical guidelines — a roadmap for project managers, knowledge managers, and organizational leaders — to prepare their environments, teams, and knowledge assets for the transition toward AI-supported knowledge management.

These guidelines address cultural, organizational, technical, and process dimensions of readiness.

5.6.2 Assess and Strengthen Knowledge Foundations

→ AI cannot create value from absent or poor-quality knowledge.

AI cannot generate meaningful value from knowledge that is absent, fragmented, or of poor quality. Its effectiveness is directly tied to the strength and structure of an organization's existing knowledge base. To lay the groundwork for successful AI integration, organizations should begin by conducting a comprehensive knowledge audit—identifying critical knowledge assets, understanding where they are located, and recognizing who holds them. Following this, it is important to map out key knowledge gaps, pinpoint areas of fragmentation, and address any entrenched silos that may impede information flow. Establishing consistent and standardized documentation practices further ensures that knowledge is accessible, transferable, and ready for AI-enabled processes. Finally, promoting a culture of knowledge sharing well before the introduction of AI helps build the collaborative habits and open environment necessary for intelligent systems to thrive.

Organizations should:

- Conduct a knowledge audit: Identify critical knowledge assets, where they are, and who holds them.
- Map key knowledge gaps, silos, or areas of fragmentation.
- Standardize documentation practices.
- Promote a culture of knowledge sharing long before AI enters.

5.6.3 Structure and Clean Organizational Data

→ AI thrives on structured, clean, and connected data.

AI thrives on data that is structured, clean, and meaningfully connected. To ensure that AI systems can operate effectively, organizations should first focus on organizing project records, reports, risk logs, and lessons learned into accessible and standardized formats. This not only improves retrievability but also sets the stage for consistent analysis. In parallel, it is crucial to eliminate redundant, outdated, or trivial information that may clutter the knowledge base and reduce signal quality. Consistent tagging and categorization of content further enhance searchability and alignment across systems. Additionally, establishing clear metadata standards for all knowledge artifacts ensures that information can be interpreted and utilized accurately by AI tools, paving the way for more intelligent and reliable insights.

Steps to take:

- Organize project records, reports, risk logs, lessons learned in accessible formats.
- Eliminate redundant, outdated, or trivial information.
- Tag and categorize content consistently.
- Create metadata standards for knowledge artifacts.

5.6.4 Digitize Tacit Knowledge

→ Tacit knowledge (from senior experts, project veterans) must be externalized.

Tacit knowledge, often held by senior experts and experienced project veterans, represents a critical yet frequently underutilized asset. To fully leverage this knowledge, it must be externalized in ways that make it accessible and usable across the organization. One effective approach is to conduct structured interviews with key experts, allowing their insights to be systematically captured. Recording and summarizing project debrief sessions can also help preserve valuable experiential knowledge that might otherwise be lost. Encouraging the use of collaborative platforms facilitates ongoing experience-sharing among team members, fostering a culture of collective learning. Importantly, efforts to externalize tacit knowledge should focus on capturing rich narratives and contextual understanding, not just numerical data, to provide deeper insights that support decision-making and innovation.

Practical actions:

- Conduct structured interviews with key experts.
- Record and summarize project debrief sessions.
- Use collaborative platforms for experience-sharing.
- Capture narratives, not just numbers.

5.6.5 Prepare Teams for AI Integration

→ AI is not only technical — it's cultural.

AI integration is not solely a technical endeavor, it is equally a cultural shift. For organizations to successfully adopt an AI-enabled KM system, it is essential to clearly communicate its purpose and the value it brings to the organization. This involves not only introducing the system but also providing comprehensive training to help users understand its benefits and how to use it effectively. At the same time, it's important to acknowledge and address common concerns, particularly fears about AI replacing human roles. Framing AI as a supportive assistant rather than a threat helps build trust and encourages adoption, fostering a collaborative environment where human expertise and intelligent systems can work in tandem.

Organizations should:

- Communicate the purpose of the AI-KM system clearly.
- Train users on its benefits and usage.
- Address fears about AI replacing human roles.
- Promote AI as an assistant, not a threat.

5.6.6 Design Clear Knowledge Governance Roles

→ Who owns the knowledge processes?

A crucial question in any knowledge-driven initiative is: who owns the knowledge processes? Clear ownership ensures accountability and sustained engagement. Within projects, it can be highly effective to designate KM Champions (individuals responsible for driving knowledge-related activities and fostering a knowledge-sharing mindset). For critical subject areas, assigning Knowledge Stewards helps maintain the integrity, relevance, and accessibility of domain-specific content. Additionally, establishing clear guidelines for content validation and regular updates ensures that the knowledge base remains accurate, current, and aligned with evolving project needs. Defining these roles and responsibilities is key to embedding KM practices into the organizational fabric.

Organizations should consider:

- Defining KM Champions (within projects or for the whole organization).
- Assigning Knowledge Stewards for critical domains.
- Establishing guidelines for content validation and updating.

5.6.7 Integrate AI into Existing Workflows

→ Avoid adding complexity - instead, embed AI into what people already use.

To encourage adoption and minimize resistance, it's important to avoid adding unnecessary complexity. Instead, AI should be embedded into the tools and workflows that people already use. This can be achieved by connecting the AI-enabled KM and DSS system with existing project management platforms, such as dashboards, reporting tools, and email systems. Ensuring seamless access through features like single sign-on and integrated search capabilities further reduces friction and promotes everyday use. Additionally, the system should deliver knowledge proactively through timely notifications and smart, context-aware recommendations, allowing users to receive relevant insights without having to seek them out. By meeting users where they are, AI becomes a natural extension of their workflow rather than an added burden.

Strategies:

- Connect the AI-KM DSS with project management tools (dashboards, reports, email systems).
- Ensure seamless access (single sign-on, integrated search).
- Deliver knowledge proactively (notifications, smart recommendations).

5.6.8 Start Small — Pilot and Scale Gradually

The best practice for implementing the proposed system is to begin with pilot projects, to focus on critical KM pain-points first (e.g., risk management, procurement, design history), and then try to Learn, refine, and scale based on real feedback.

5.6.9 Ensure Ethical AI Use and Transparency

Building organizational trust in AI systems requires transparency, collaboration, and user empowerment. It starts with clearly explaining how AI-generated recommendations are produced, helping users understand the rationale behind the outputs. Providing mechanisms for users to give feedback on these recommendations fosters a sense of involvement and continuous improvement. Equally important is preserving user control over decision-making—AI should act as a supportive tool, not a directive force. Ultimately, AI must enhance human judgment, not replace it, ensuring that decisions remain informed, accountable, and aligned with organizational values.

AI should support — never dictate — decisions.

5.6.10 Summary

Preparing an organization for an AI-enhanced KM Decision Support System is not only about technology readiness, it is about creating a *knowledge-ready culture*. The more structured, accessible, and valued the knowledge assets are, the greater the impact AI can have. In essence:

Technology amplifies what already exists — the quality of your KM practices today will define the success of your AI-enhanced System tomorrow.

5.7 Final Remarks

Every research journey begins with curiosity, but it should end with clarity. This thesis began with a critical observation: that despite decades of investment in Knowledge Management (KM) systems, many organizations, particularly project-based ones, still struggle not because they lack knowledge, but because they cannot activate it when it matters most. Knowledge is often fragmented, buried in documents, lost in inboxes, or simply forgotten when people leave. Yet projects (especially in dynamic, uncertain environments like Engineering, Procurement, and Construction) do not have the luxury of slow thinking or forgotten lessons.

The Core Message of This Thesis

The core proposition of this work is simple yet powerful:

Artificial Intelligence (AI), when thoughtfully integrated within a Decision Support System (DSS), can transform organizational knowledge from a static repository into a dynamic, context-aware, decision-enabling force.

Not to replace human judgment — but to *support* it.
Not to automate thinking — but to *amplify* experience.

This thesis did not chase the hype of AI. Instead, it built a bridge:

- Between classic KM practices and modern AI capabilities.
- Between theoretical models and practical project realities.
- Between organizational memory and day-to-day project life.

A Framework, but Also a Vision

What has been developed here is more than a framework. It is a vision for the future of knowledge in project environments: a future where knowledge flows like electricity through an organization, where lessons learned are never truly lost, and where every project is not just an isolated effort but part of a living, evolving organizational brain.

A Final Thought for Organizations and Researchers

In a world overwhelmed by data, competitive advantage will not belong to those who have the most information, but to those who can turn information into wisdom, at the right time, in the right context.

The future of project management belongs to organizations that can:

- Learn faster than their competitors.
- Decide smarter than their industry.
- Preserve knowledge beyond the limits of individuals or time.

This thesis offers one roadmap toward that future. But the real journey — of building, testing, refining, and evolving AI-enhanced Knowledge Management Decision Support Systems — has only just begun.

If the vision presented in this thesis is fully realized, it would be as if every project ever undertaken by our organization was completed just yesterday. All the knowledge, experiences, and lessons learned would remain fresh, readily accessible, and immediately reusable. Enabling teams to build on past insights with clarity and confidence, rather than starting from scratch each time. In the end, it is not technology alone that makes an organization intelligent. It is the way knowledge moves within it — continuously, openly, and with purpose.

"If we only knew what we know, we would be twice as profitable."

— **Davenport and Prusak (1998)** [43]

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