AI for Comprehensive Naval Project Management: From Render to Launch

DOI: 10.25043/19098642.276

Diego Cortés [1]
Karol León [2]

Abstract

The integration of generative Artificial Intelligence (AI) tools is transforming project management in the naval industry. This article proposes the design of a comprehensive management system for naval design and engineering projects that incorporates AI and machine learning technologies in each phase of the project life cycle. Using Adaptive Structuration Theory (AST), the study examines how design project managers implement these tools to optimize processes from conceptualization to delivery. Factors such as Innovative Attitude, Peer Influence, and Task-Technology Fit (TTF) are considered. The proposed system includes modules for document analysis, activity planning, cost and timeline forecasting, and risk and requirements management, all powered by AI. An integration plan and evaluation framework are presented to measure the potential impact of the system on the efficiency and effectiveness of naval project management. This study offers a significant contribution to the understanding how generative AI can transform project management in the naval industry, while addressing the associated ethical and practical challenges.

Key words: Artificial Intelligence (AI), Naval Project Management, Project Efficiency, Adaptive Structuration Theory (AST).

How to cite this article
To cite this article, use the following format:

IEE Format
[1] JD. Cortés and K. León, "AI for Comprehensive Naval Project Management: From Render to Launch" Ship Science and Technology (Cartagena), vol. 19, no. 37, pp. 75-108, 2025. DOI: https://doi.org/10.25043/19098642.276

Date Received: November 23rd, 2024
Date Accepted: December 9th, 2024
Publication Date: November 2nd, 2025

COTECMAR, Colombia. ROR: https://ror.org/01z04wv09
[1] Email: dcortes@cotecmar.com ORCID: https://orcid.org/0000-0003-1959-0162
[2] Email: kleon@cotecmar.com ORCID: https://orcid.org/0000-0001-5838-851X

DOI: 10.25043/19098642.276

Introduction

The naval industry stands at a critical inflection point, facing unprecedented project management challenges due to the increasing complexity of modern vessels and the demand for shorter production cycles. These projects, spanning from conceptual design to final delivery, are characterized by an intricate web of interdependencies between design, engineering, procurement and construction, requiring precise and efficient coordination for success. Traditional project management, often based on linear and waterfall planning, is challenged by the dynamic and iterative nature of modern naval projects, where changes in requirements, technology or the market are frequent and require high adaptability. [1], [2]

In this context, generative Artificial Intelligence (AI) is emerging as a disruptive technology with the potential to revolutionize project management in the naval industry. Generative AI tools, such as chatbots, predictive analytics systems and AI-powered project management platforms, provide the ability to automate tasks, optimize resources, improve decision making and manage risks proactively. [3], [4] Unlike traditional AI, which focuses on analysis and prediction, generative AI creates original content and innovative solutions, opening up new possibilities for naval project management. [5], [6]

However, the integration of generative AI in the naval industry is not without its challenges. Naval project management is characterized by the need to handle large volumes of technical documentation, coordinate multidisciplinary teams and adapt to international regulations. Moreover, the conservative nature of the naval industry often resists to the adoption of new technologies. [7], [8] Therefore, it is critical to understand how these factors can impact the implementation and effective use of AI in this specific context.

This paper addresses the need for a comprehensive management system for naval design and engineering projects that incorporates generative AI to overcome traditional management challenges and maximize the potential of this technology. The proposed system uses Adaptive Structuration Theory (AST) as a theoretical framework to understand the interaction between people and advanced technologies in organizations. [9], [10] Furthermore, individual and contextual factors, such as innovative attitude, peer influence, and task-technology fit, are taken into account to analyze the appropriation and use of AI by project managers. [11], [12] The system integrates modules for document analysis, planning, forecasting and risk management, all powered by AI, with the purpose of improving efficiency, accuracy and proactive project management.

Finally, this paper not only contributes to the theoretical understanding of the application of generative AI in naval project management, but also provides practical information for the industry and sets a solid foundation for future research. The discussion focuses on project management from the design phase to ship launch, addressing the ethical and implementation challenges of AI to foster a human-centered approach.

State of the Art

This section presents a review of relevant literature to contextualize the research and highlight the need for a naval project management system with generative AI. The following areas are discussed:

A. AI and Machine Learning in project management

AI and machine learning (ML) have transformed project management in various industries. AI technologies, including deep learning (DL), natural language processing (NLP), and computer vision, are applied in various project phases, from planning and monitoring to risk management and decision making. [13], [14] These technologies allow automating tasks, optimizing resource allocation, predicting results, and improving communication among team members. [15] However, the application of AI in project management also brings along certain challenges, such as the need for large datasets, model interpretability, and bias management. [16] In the naval context, AI has been used to optimize routes, predict equipment maintenance, and improve safety. [17] However, its potential for integrating generative AI into comprehensive project management has yet to be fully explored.

B. Naval project management

Managing naval projects poses unique challenges due to the complexity of modern ships, tight deadlines and strict regulations. These projects often involve a large number of stakeholders, from engineers and designers to shipyards and clients, requiring efficient communication and collaboration management. [18] Traditional project management, with its linear approach, often fails to adapt to the frequent changes that occur during the project lifecycle. [11] The integration of generative AI offers the potential to address these challenges by automating tasks, optimizing resources, and proactively managing risks, improving efficiency and accuracy in naval project management.

C. Technological Appropriation in the Naval Industry

The adoption of new technologies in the traditionally conservative naval industry is influenced by organizational, individual and technological factors. [8] At the organizational level, company culture, management support and resource availability play a crucial role. At the individual level, innovative attitude, peer influence and self-efficacy are determining factors. [11] The complexity of naval systems and the need for integration with existing systems also influence technology adoption. [11] Models such as the Technology Acceptance Theory (TAM) and the Use and Gratification (U&G) Model have been used to understand technology adoption in this sector. [8] However, a deeper understanding of how these factors interact to influence the appropriation of generative AI in naval project management is needed.

D. Project Management Systems with AI

There are several project management systems (PMSs) that incorporate AI, offering functionalities such as data analysis, risk prediction, and resource optimization. [12] These systems are based on different architectures, from cloud-based systems to on-premises solutions, and use a variety of AI technologies, including ML, NLP, and computer vision. While these systems have proven to be beneficial in project management in other sectors, their application in the naval industry is still limited. Furthermore, the integration of generative AI into these systems entails specific challenges, such as the need to adapt the algorithms to naval terminology and the management of uncertainty inherent in naval projects. [19]

This literature review underscores the need for a project management system that integrates generative AI, addressing the complexity and specific challenges of the naval industry. The system proposed in this paper seeks to fill this gap, offering an innovative solution to improve efficiency, accuracy and proactive project management, from design to launch.

Methodology

System Design

The proposed system adopts a modular architecture based on microservices, distributed in four interconnected layers that communicate through an application programming interface with a Representational State Transfer (RESTful API) design protocol and an event bus.

This architecture, inspired by robust and scalable enterprise management systems [20], provides flexibility, maintainability and a good fit between components. In addition, it allows integration with legacy systems and adaptation to the changing needs of the naval industry.

General architecture

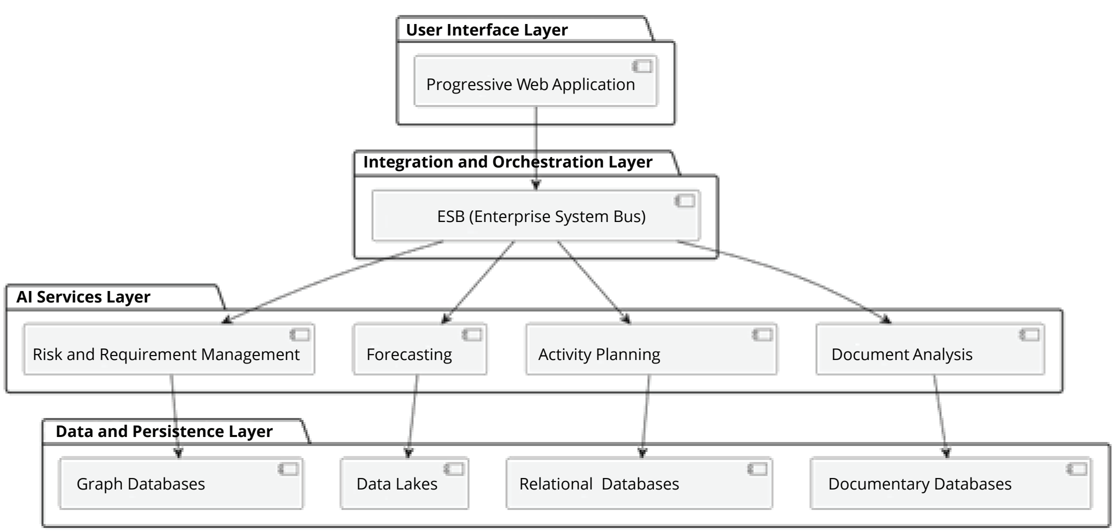
The naval project management system architecture is made up of four interconnected layers. The user interface layer, UX, designed as a Progressive Web Application (PWA), enables access from any device, offering a consistent user experience and improving accessibility in industrial environments. This layer provides a centralized view of the project, including schedule, resources, risks and progress, enabling real-time monitoring and management. The IA Services layer, the core of the system, consists of four independent modules (document analysis, activity planning, forecasting, and risk and requirements management) that communicate through an enterprise service bus (ESB) to ensure information consistency and dependency management. The Integration and Orchestration layer, also managed by the ESB, facilitates integration with external systems such as Enterprise Resource Planning (ERP) and Computer Aided Drafting (CAD), enabling data synchronization and messaging between modules. The Data and Persistence layer uses a polyglot storage approach, combining relational, document, graph and data lake databases to efficiently manage diverse project data. The system also implements a Role-Based Security Model (RBAC) with multi-factor authentication and a logging and monitoring system to ensure security and performance tracking.

Detailed description of each module

Each module of the AI Services layer has been designed to address a specific aspect of naval project management, using specific AI algorithms and technologies. Communication between the modules is achieved through the ESB, ensuring a smooth workflow and dependency management. Each module is described in detail below:

A. Document Analysis Module: This module automatically processes and analyzes technical documentation using Natural Language Processing (NLP) techniques. It uses a specific version of the Bidirectional Encoder Representations from Transformers (BERT) model, tailored to the naval industry, which has

Fig. 1. Project Management System Architecture.



demonstrated high accuracy (over 89%) in the extraction of relevant information [13], [21]. This model, based on transformers, enables a contextualized understanding of language, overcoming the limitations of traditional sequence-based models. The main functionalities of the module include the extraction of technical specifications, the classification of documents according to the standard naval taxonomy, the identification of regulatory requirements and the detection of inconsistencies in documentation. The module uses Named Entity Recognition (NER) to identify and classify specific entities in the naval field, such as ship types, equipment and materials. Input data are technical documents in digital format, while output data are structured data sets containing relevant extracted information such as specifications, requirements and possible inconsistencies.

B. Activity Planning Module: This module is responsible for the planning and scheduling of project activities, taking into account resource constraints, deadlines and interdependencies between tasks. The module uses a hybrid system that combines historical data analysis with optimization algorithms, such as genetic algorithms, to generate optimized plans tailored to the specific needs of each project. [11], [22] A historical data analysis engine, based on Apache Spark, processes large volumes of data to identify patterns and trends. Genetic algorithms are applied to optimize activity sequencing and resource allocation, taking into account project constraints. The module also includes a resource balancing system to ensure efficient workload distribution and an interface for the manual adjustment of plans, allowing project manager intervention when necessary. Input data include the project's SWBS (Ship Work Breakdown Structure), resource availability, timelines and historical data from similar projects. Output data are optimized project plans, including the sequence of activities, resource allocation and schedule.

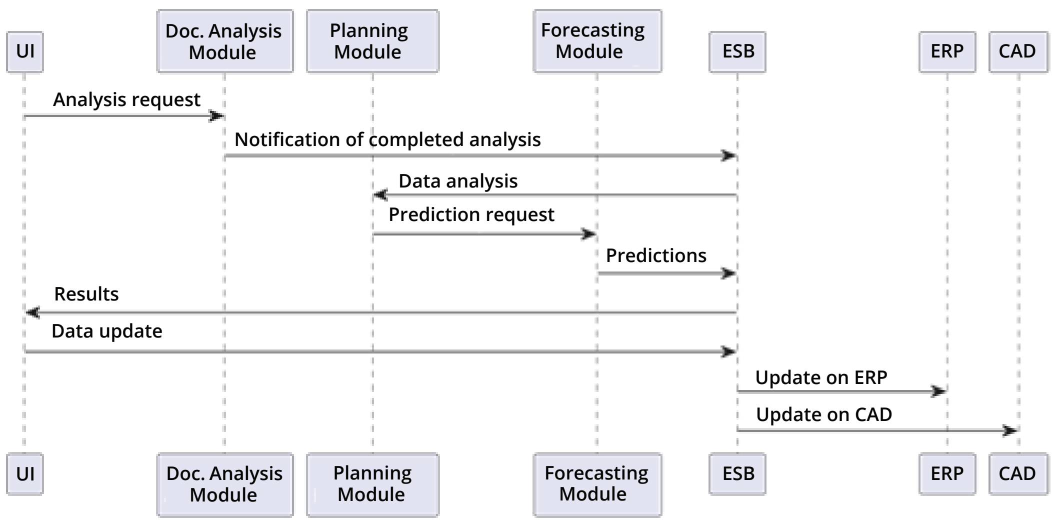
C. Forecasting Module: This module generates predictions on project cost and duration using predictive models based on LSTM (Long Short-Term Memory) neural networks. [11], [23] LSTM networks, a type of recurrent neural network, are particularly suitable for time series analysis and have demonstrated high accuracy in predicting costs and timelines in complex projects. The module analyzes historical data from similar projects, considering variables specific to the naval industry, such as weather conditions and availability of resources (dry docks, skilled labor, etc.). In addition, the module performs trend analysis to identify possible deviations from the plan and generate early warnings. Input data include historical project data, such as costs, deadlines and resources used, as well as relevant environmental data, such as market conditions and regulations. Output data are predictions on project cost and duration, as well as an analysis of risks and opportunities.

D. Risk and Requirements Management Module: This module is responsible for proactive risk identification and management, as well as for the traceability of project requirements. It uses machine learning (ML) algorithms to identify patterns in historical project data and detect potential emerging risks. [24] It also uses knowledge graphs to represent the relationships between requirements and risks, facilitating traceability and impact analysis. [25] A continuous risk monitoring system enables proactive management and the implementation of mitigation measures. Input data include historical project data, such as identified risks and their impacts, as well as project requirements and their interdependencies. Output data are risk assessments, mitigation plans and a log of requirements traceability.

Integration between modules

The modules of the AI Services layer are integrated with external systems through a combination of RESTful APIs and an event bus, following the Event Driven Architecture (EDA) pattern. This architecture enables asynchronous communication between modules, which means that they do not need to be constantly connected to each other, but can exchange information independently through the event bus.

Fig. 2. Sequence Diagram.



The combination of RESTful APIs and EDA offers several advantages for integration between modules:

- Loose coupling: Modules do not need to know the internal implementation of other modules, which facilitates their independent development and maintenance.
- Scalability: Each module can be scaled independently to adapt to the demands of the system.
- Flexibility: The system can easily adapt to changes in requirements or technology.
- Resilience: The failure of a module does not affect the operation of the rest of the system.
- Traceability: The event bus logs all published events, facilitating traceability of operations and identification of potential problems.

This integration approach, based on RESTful APIs and EDA, lays a solid foundation for a robust, scalable, flexible and resilient naval project management system, facilitating the integration of generative AI and the efficient management of complex projects.

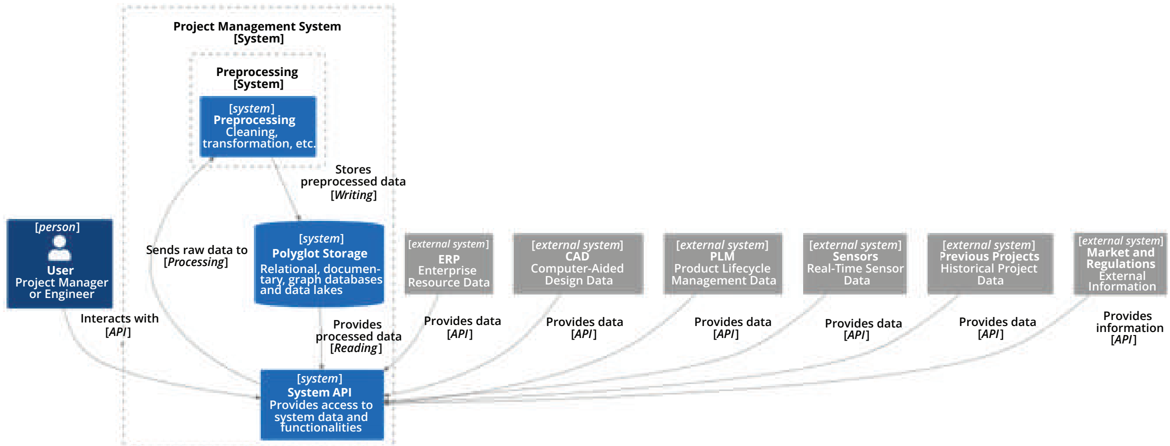
Data

Efficient data management is paramount for the proper operation of the project management system. This system uses a variety of data sources, which are integrated and processed to provide relevant information to the various modules.

Data sources

The system draws from a variety of data sources, both internal and external, to capture a full picture of the project. The main data sources include:

Fig. 3. Data Sources.



The integration of these various data sources provides a holistic view of the project, for more efficient and accurate management. The system uses data integration techniques to combine data from different sources and formats, ensuring information consistency and quality.

Data Preprocessing

Before the data can be used by the different modules of the system, it undergoes a preprocessing process to ensure its quality, consistency and compatibility. Data preprocessing is a crucial step in any AI project, and naval project management is no exception. [16] Data, coming from various sources and in different formats, can contain errors, inconsistencies, missing values, and noise, which can negatively impact the performance of AI models and the accuracy of results.

Data preprocessing is an iterative process that is performed in collaboration with field experts to ensure that the data is accurate, consistent and relevant to the needs of the project. Thorough data preprocessing is essential to the success of the project management system, ensuring the quality of the data used to train the AI models and the accuracy of the results obtained.

Data model

The system's data architecture is based on a polyglot model, which brings together different types of databases to take capitalize on the benefits of each and adapt to the wide array of data used in naval project management. This approach is instrumental to efficiently manage information, from structured to unstructured data, and to facilitate analysis and knowledge extraction using AI techniques. The selection of a polyglot data model is essential for projects involving large volumes of heterogeneous data, such as naval project management, and follows current trends in data management for AI. [26] It also facilitates system scalability and flexibility, allowing adaptation to changing project needs.

The system uses the following types of databases:

A. Relational databases: They are used to store structured project data, such as task, resource, timeline and cost information. Their rigid structure and predefined schema ensure data consistency and integrity, which is essential for project planning and control. In addition, relational databases provide high query and transaction performance, which is important for a real-time project management system. In this system, relational databases are used to store information from the ERP, such as resource availability and costs.

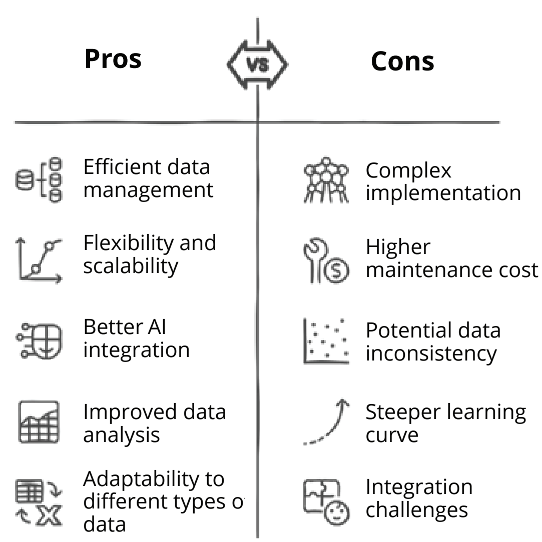
B. Document databases: They are used to store technical specifications and other project documents. Their flexible schema allows storing unstructured or semi-structured information, such as text, images and videos. This is especially useful for document management, where flexibility and full-text searchability are essential. In this system, document databases are used to store information from the CAD system, such as drawings, 3D models and technical specifications. This choice is justified by the need to access contextualized information to, for example, identify the causes of design delays [19] or predict the need for specialized human resources based on the type of vessel and technologies involved. The ability of generative AI to process natural language and understand the context of documents is key to extract relevant information and improve the accuracy of predictions.

C. Graph databases: They are used to represent the relationships between requirements, risks and other project elements. Their structure based on nodes and relationships makes it possible to represent the complex interdependencies between the different elements of the project, which facilitates impact analysis and risk management. This graphical representation is key for information traceability, change management and the identification of potential risks. In the context of generative AI adoption, graph databases are essential for modeling the complex relationships between project requirements and AI capabilities, for a better expectation management and greater efficiency in the implementation of generative AI solutions.

D. Data Lakes: They are used to store large volumes of historical data, both structured and unstructured. These data are used for AI model training, trend analysis and pattern identification. Data lakes provide a flexible and scalable platform for data storage, which is essential for projects that generate large volumes of information over time. The ability to store raw data without a predefined schema allows to fully leverage the potential of generative AI to uncover hidden patterns and generate new insights, driving innovation in ship design.

The combination of these different types of databases in a polyglot architecture allows for an efficient and flexible management of project information, adapting to the specific needs of each module and to the characteristics of the data. This flexibility is crucial for the integration of generative AI in naval project management, enabling the development of innovative solutions and the optimization of design and construction processes.

Fig. 4. Polyglot data model in ship project management.



Implementation

The implementation phase focuses on the materialization of the system, translating the architectural design into a functional system. This phase involves the selection of specific technologies, the structuring for code development, the concept of module integration and the design of system tests. Implementation must be done iteratively, with development, testing and feedback cycles to ensure quality and compliance with requirements.

Technologies used

The selection of technologies is based on criteria of performance, scalability, maintainability, security and compatibility with existing systems. The system will be implemented using the following technologies:

A. Programming language: Python, for its versatility, wide set of AI libraries and ease of integration with other technologies. Python is a high-level interpreted language, widely used in the development of AI and machine learning applications. [27] Its clear and concise syntax makes it easy to write and maintain code, while its extensive ecosystem of libraries provides tools for a variety of tasks, such as natural language processing, data analysis and visualization.

B. Frameworks: Several frameworks are selected for the development of the various modules of the system. The spaCy framework is used for the Document Analysis module, which is a NLP library for Python that provides functionalities for natural language processing, such as parsing, entity tagging, and information extraction. [28] The Optuna framework is used for the Activity Planning module, which is an automated optimization framework for Python that facilitates the search for optimal hyperparameters for machine learning models. [29] The PyTorch Forecasting framework is used for the Forecasting module, which is a time series forecasting framework for PyTorch that provides functionalities for the development and training of LSTM models. [30] The Neo4j framework is used for the Risk and Requirements Management module, which is a graph database that allows representing and analyzing the relationships between requirements, risks and other project elements. [31] The selection of these frameworks is based on their performance, scalability, ease of use and adaptation to the specific needs of each module.

C. Libraries: Several libraries are required to supplement the frameworks' functionalities. These libraries provide tools for specific tasks, such as data preprocessing, visualization and model management. Some examples of libraries to integrate are Pandas and NumPy for data analysis, Matplotlib and Seaborn for visualization and MLflow for model management. [32]-[34] The selection of these libraries is based on their performance, ease of use and adaptation to the specific needs of each module.

D. Database: The system is conceptualized with a polyglot data architecture, combining relational, document, and graph databases to efficiently manage the multiplicity of data inherent in naval project management. [31] PostgreSQL, a robust and scalable open source relational database management system, is used to store structured project data such as task, resource, timeline, and cost information. [35] MongoDB, a NoSQL document database, is used to store unstructured or semi-structured information, such as technical specifications, blueprints and 3D models, providing flexibility and efficiency in document management. [36] Neo4j, a graph database, is used to represent the relationships between requirements, risks and other project elements, facilitating impact analysis and risk management. [31] This combination of databases enables efficient and secure data management, adapting to the different formats and requirements of each type of information, while taking advantage of the specific benefits of each technology.

E. Event bus: Apache Kafka is chosen as the event bus for asynchronous communication between modules. Apache Kafka is a distributed, high-performance and scalable streaming platform, which enables efficient management of large volumes of real-time data. [37]

F. Containerization: For the containerization of modules and their dependencies Docker is the chosen option, as it facilitates the deployment and management of applications, ensuring the portability and consistency of the execution environment. [38]

G. Orchestration: Kubernetes is selected for the orchestration of Docker containers, automating the deployment, scalability and management of applications in a distributed environment. [39]

The blend of these technologies lays a solid foundation for system implementation, ensuring performance, scalability, maintainability and security. The preference for open source technologies facilitates collaboration and adaptation to the specific needs of the project.

Development Environment

Optimizing the implementation of the system and seeking to ensure quality, efficiency and responsiveness to changes, we chose to structure an agile and iterative development environment. This approach, widely adopted in modern software development, follows the dynamic nature of AI projects and allows for an agile adaptation to new technologies and evolving requirements. [40] Version management is achieved through a Git repository, which facilitates collaboration between developers and change tracking. To automate the software building, testing and integration process, a continuous integration server is implemented.

System Testing and Validation

The system testing and validation phase, which is essential to ensure design quality, reliability and robustness, was planned with a comprehensive and iterative approach, integrating various techniques to cover all system components and functionalities. While full implementation and performance testing is beyond the scope of this design-focused article, this subsection describes the planned validation strategy for the system once implemented.

Unit tests will be defined for each module of the AI Services layer, using frameworks such as Pytest for Python modules. [41] These tests will be designed to verify the performance of each unit of code in isolation, ensuring that the functions and methods produce the expected results according to the design specifications. A set of test cases covering different scenarios and inputs will be developed, with the objective of detecting possible errors or inconsistencies in the logic of each module.

System evaluation

The evaluation of the system, which is fundamental to determine the effectiveness of the proposed design and its ability to improve the productivity of the design and engineering office, was planned using a dual approach: efficiency metrics and effectiveness indicators. This comprehensive approach will allow not only quantifying the performance of the system, but also assessing its impact on naval project management. Since this paper focuses on the design of the system, the evaluation is intended as a proposal for the post-implementation stage.

Efficiency Metrics

Efficiency metrics will focus on quantifying system performance in terms of time, accuracy and resource utilization, key aspects of design and engineering office productivity. An efficient system will allow engineers to spend more time on higher value-added tasks, such as creative design and complex problem solving, rather than repetitive, low-value tasks.

The following efficiency metrics, categorized into three groups, are proposed:

A. Temporal Performance Metrics: These metrics will measure the speed and responsiveness of the system, which are crucial aspects for the productivity of professionals.

Reduced planning time (%): This metric will measure time savings in project planning due to the task automation and resource optimization provided by the system. A meaningful reduction in planning time will translate into increased productivity of the design and engineering office.

Document processing speed (pages/minute): This metric will measure the speed at which the Document Analysis module processes technical documentation. A higher processing speed will allow engineers to access relevant information faster, improving their productivity.

B. Accuracy Metrics: These metrics will focus on the accuracy and reliability of the results produced by the system, which is fundamental for informed decision making.

Cost estimating accuracy (%): This metric will measure the accuracy of the Forecasting module in estimating project costs. Higher estimating accuracy will allow engineers to make more informed budgeting decisions.

Requirements identification accuracy (%): This metric will measure the accuracy of the Document Analysis module in identifying project requirements. Greater accuracy in identifying requirements will allow engineers to ensure that the vessel design meets the client's specifications.

Risk detection false positive rate (%): This metric will measure the false positive rate of the Risk and Requirements Management module. A low false positive rate is key to prevent engineers from spending time analyzing risks that are not real.

Document classification accuracy (%): This metric will measure the accuracy of the Document Analysis module in classifying technical documentation. An accurate classification will facilitate the search and retrieval of relevant information.

C. Resource Utilization Metrics: These metrics will measure the efficiency of the system in the utilization of computational resources, such as CPU, memory and storage.

Computational resource consumption (CPU/RAM): This metric will measure the amount of computational resources used by the system. An efficient use of resources will reduce operating costs and improve system performance.

Data storage efficiency (GB): This metric will measure the efficiency of the system in managing storage space. An efficient storage management will reduce costs and improve system scalability.

The application of these metrics will allow quantifying system performance and assess its impact on the productivity of the design and engineering office, a key objective of the AI-powered project management system.

Effectiveness Indicators

As a complement to efficiency metrics, effectiveness indicators will focus on assessing the impact of the system design on project management, decision making, user satisfaction and the value generated for the organization. These more qualitative indicators will provide a holistic view of the benefits of the system and its ability to achieve its stated objectives, including improved productivity of the design and engineering office. As with the efficiency metrics, these indicators are proposed as part of the post-implementation evaluation plan.

For a full evaluation, the following effectiveness indicators are proposed, grouped into four components:

a) Impact on Project Management: These indicators will measure how the system design impacts the efficiency and effectiveness of naval project management.

Timeline deviation reduction (%): This indicator will measure the system's ability to help project managers keep projects on schedule. By providing real-time information, accurate forecasts and optimization tools, the system is expected to reduce deviations and improve schedule adherence.

Improved accuracy of budget estimates (%): This indicator will assess the system's ability to generate more accurate budget estimates, as a result of the integration of historical data, risk analysis and forecasting capabilities. Improved accuracy in budget estimates is expected to reduce cost overruns and improve efficiency in resource allocation.

Reduced unplanned modifications (%): This indicator will measure the system's ability to reduce the need for unplanned modifications to the project through better planning, more proactive risk management and more efficient communication. A reduction in unplanned modifications is expected to improve efficiency and reduce project costs.

Increased early risk detection (%): This indicator will assess the system's ability to help project managers identify potential risks early. It is expected that early risk detection will enable project managers to take preventive action and avoid potential delays or cost overruns.

b) Improved Decision Making: These indicators will assess how the system supports informed and strategic decision making.

Reduced critical decision making time (%): This indicator will measure the system's ability to speed up the decision making process, especially at critical moments in the project. It is expected that the system, by providing relevant information and analysis tools, will reduce the time required to make decisions and improve project management efficiency.

Increased data-driven decisions (%): This indicator will measure the degree to which the system enables data-driven decision making. It is expected that the system, by providing real-time information, predictive analytics and visualization tools, will increase the quantity of data-driven decisions and improve the quality of those decisions.

Improved quality of strategic decisions (scale 1-5): This indicator will assess the system's impact on the quality of strategic decisions. It is expected that the system, by providing a holistic view of the project and scenario analysis tools, will improve the quality of strategic decisions and their alignment with the organization's objectives.

c) User Satisfaction: These indicators will measure the level of user satisfaction with the system design, a key factor for its adoption and effective use.

End-user satisfaction index (scale 1-10): This indicator will measure overall user satisfaction with the system, using a scale of 1-10, where 10 represents maximum satisfaction.

System adoption rate (%): This indicator will measure the percentage of users who adopt and use the system. A high adoption rate will indicate that the system is perceived as useful and easy to use.

Frequency of use of advanced functionalities (%): This indicator will measure the frequency with which users use the advanced functionalities of the system. A high usage of advanced functionalities will indicate that the system provides valuable tools for project management.

Average time to adapt to the system (days): This indicator will measure the time it takes for users to adapt to the system and use it effectively. A short adaptation time will indicate that the system is easy to learn and use.

d) Business Value: These indicators will measure the value generated by the system for the organization, in terms of return on investment, cost reduction and performance improvement.

Return on Investment (ROI) (%): This indicator will measure the return on the investment in the system, comparing the benefits produced with implementation costs. A positive ROI will indicate that the system is a profitable investment for the organization.

Reduced operating costs (%): This indicator will measure the system's ability to reduce project management operating costs. Task automation, resource optimization and improved efficiency are expected to reduce operating costs.

Improved meeting of contractual deadlines (%): This indicator will measure the system's ability to improve compliance with contractual deadlines. Better planning, more proactive risk management and more efficient communication are expected to improve schedule adherence.

Increased ability to manage concurrent projects (%): This indicator will measure the system's ability to help the organization manage a greater number of projects simultaneously. It is expected that the system, by providing planning, monitoring and control tools, will increase the organization's ability to manage projects simultaneously and improve resource allocation efficiency.

These indicators, along with efficiency metrics, will provide a full picture of the effectiveness of the system design and its ability to achieve the stated objectives, including improved productivity of the design and engineering office.

Measurement Methodology

For a robust and comprehensive evaluation of the system design, a blended measurement methodology will be implemented, combining automatic data collection with manual evaluation. [42] This hybrid approach, widely used in complex systems research, allows capturing both quantitative data on system performance and qualitative information on user experience and the impact of the design on the organization. [43]

Automated measurement will be performed through real-time system monitoring and log analysis. Automated tools will be used to collect data on efficiency metrics such as planning time, system response time and document processing speed. Log analysis will provide information on errors and exceptions, which will identify areas for design improvement. Tools such as Prometheus and Grafana will be used for monitoring and visualizing efficiency metrics. [44], [45]

Manual evaluation will be performed through different methods, such as satisfaction surveys, interviews with key users and expert evaluations. Satisfaction surveys will allow collecting data on system usability and user experience. [46] Key user interviews will provide detailed information on the impact of the design on project management, decision making and the value generated for the organization. Expert evaluations will be used to validate system architecture, technology selection, and design quality. [47] Heuristic evaluation frameworks will be used to guide expert evaluations and recommendations for future improvements will be documented.

The combination of automatic measurement and manual evaluation will provide a comprehensive view of the system design, for an objective and thorough assessment of its efficiency, effectiveness and impact on the organization. This blended approach is key to validate the system design and ensure its ability to achieve the stated objectives, including improving the productivity of the design and engineering office.

Benchmarking and Success Criteria

To evaluate the performance of the AI project management system and ensure its ability to attain the proposed objectives, benchmarks and success criteria will be established to compare its performance with other project management solutions, both traditional and AI-based, used in the naval industry. Systems with similar functionalities will be selected for a fair and objective comparison, using previously defined efficiency metrics and effectiveness indicators. Furthermore, an analysis of best practices in naval project management will be carried out to identify areas for improvement and opportunities for innovation. A continuous evaluation plan will be implemented that will include real-time monitoring of efficiency metrics, periodic evaluations and collection of user feedback. This approach will identify areas for improvement and make adjustments to ensure the long-term efficiency and effectiveness of the system, ensuring its adaptation to the changing needs of the naval industry.

Continuous Evaluation Plan

To ensure the effectiveness and continuous adaptation of the system to the changing needs of the naval industry, a continuous post-implementation evaluation plan will be put in place. This plan, based on an iterative feedback loop [48], will allow monitoring the performance of the system, identify areas for improvement, and ensure its long-term adaptation. Continuous evaluation is instrumental in AI projects, where technology and requirements evolve rapidly, and is consistent with best practices for adaptive system development. [49]

This continuous evaluation plan will monitor the system's performance over time, identify areas for improvement, ensure its adaptation to the changing needs of the naval industry and maximize its impact on the productivity of the design and engineering office.

AST-based Appropriation Model

To understand how project managers appropriate and use the AI project management system, Adaptive Structuration Theory (AST) will be used. [9] AST provides a theoretical framework for understanding how individuals and organizations interact with technologies, adapting them to their needs and practices. [50] This framework is particularly relevant in the context of generative AI, where technology flexibility and adaptability underlay its effective appropriation.

Innovative Attitude Factors

The innovative attitude of project managers, a key individual factor in the appropriation of new technologies [51], will be assessed by considering three main components: willingness to technological change, digital competence and value perception. These components, stemming from the technology adoption literature [52], reflect individuals' beliefs, skills and motivations towards technology. It is crucial to understand these components in order to design a system that is not only efficient and accurate, but also attractive and easy to use for project managers, thus encouraging long-term ownership and use. The goal is for users to perceive the system as a tool that enhances their skills, rather than replacing them, freeing them from repetitive tasks so that they can concentrate on higher value-added activities. [11], [53] The premise is that a system that is perceived as supporting creativity and complex problem solving, rather than as a threat to the job, will have a greater likelihood of being adopted and integrated into design office practices.

This focuses on three key components: readiness for technological change, digital competence and perceived value. Readiness for technological change measures the openness and willingness to adopt new technologies in work, assessing the acceptance of AI, willingness to learn new tools, and tolerance for technological risk. Digital competence assesses the skills and knowledge in using digital technologies, including the experience with project management software, AI tools and data analytics. Perception of value, crucial to system adoption, focuses on how managers perceive the usefulness, ease of use, impact on efficiency and productivity, and contribution to innovation of the system. This component seeks to ensure that the system is seen as a tool that enhances engineers' skills, allowing them to focus on creative and complex tasks. Taken together, these assessments identify the motivations and barriers to adoption of the system, and adjust its design to maximize its perceived value, thus facilitating its successful integration into AI project management practice.

Peer Influence

Peer influence, a key contextual factor in the appropriation of new technologies [54], will be assessed through the components of support networks, group dynamics and leadership. These components, stemming from the literature on social psychology and organizational behavior [55], [56], illustrate how social interactions and group norms shape the adoption and use of new technologies. Understanding these dynamics is essential to design a system that promotes collaboration, knowledge sharing, and mutual support among designers, thus maximizing the potential of generative AI for innovation and problem solving. It is intended that designers perceive the system as a tool that facilitates their creative work, not as a source of pressure or competition. The active participation of designers, who generate key data through the activity log (production spreadsheet), is essential to foster ownership and collaboration around the system.

Support networks will be analyzed by considering the existence of communities of practice, expert groups, mentors and other forms of informal support within the organization. Group dynamics will be assessed in terms of how norms, team cohesion and leadership influence system adoption, including social pressure and innovation culture. Finally, the role of leadership will be examined in terms of supporting system adoption, communicating its benefits, and managing organizational change. Transformational leadership [22] that promotes a shared vision, drives innovation, and effectively manages resistance to change will be critical to the successful adoption of the system. The assessment of these components will enable the design to be tailored to bolster collaboration and knowledge sharing, increasing the likelihood of system adoption and its contribution to innovation in ship design.

Task-Technology Fit (TTF)

Task-Technology Fit (TTF), a key factor in the acceptance and use of new systems [57], will be evaluated by considering the correspondence between the designers' task characteristics, the system capabilities, and the functional fit between the two. This framework, derived from the TTF model [58], examines how technology aligns with users' needs and workflows. In the context of naval project management, it is crucial that the system is tailored to designers' specific tasks, such as activity reporting, document analysis, and CAD model generation, to facilitate their integration into the design office. The main objective is to minimize friction between technology and existing work practices, promoting efficiency and productivity. A fundamental aspect is to facilitate the adaptation of designers to the reporting of their daily activities, as this information is key to system learning and process optimization.

The assessment of TTF requires an in-depth analysis of multiple interrelated components. First, task characteristics involve the specific aspects of designers' work in the management of naval projects, encompassing the inherent complexity of projects, interdependencies between activities, collaboration and communication requirements, and the extensive handling of technical documentation. A particularly critical aspect is the adaptation of designers to the reporting of their daily activities through the production spreadsheet, considering that this information is fundamental for system learning and continuous process optimization. [11]

The technological capabilities of the system constitute another essential dimension, matching its functionalities for document analysis, activity planning, forecasting and risk management, as well as its ability to integrate with pre-existing tools, particularly CAD systems. The evaluation of these capabilities should consider the system's potential to automate routine tasks, optimize resource allocation, improve decision-making processes and facilitate effective collaboration among team members.

Functional fit, as the third fundamental component, evaluates the correspondence between the characteristics of the tasks and the technological capabilities of the system. This analysis is key to determine whether the system effectively adapts to established workflows, whether it delivers an intuitive and accessible interface, and whether it provides the tools and information necessary for efficient task execution. Seamless integration with existing CAD tools and the system's ability to automate the analysis of technical documents are considered key aspects to ensure successful adoption by designers. [19]

The TTF assessment will allow tailoring the system design to the specific needs of designers, minimizing friction between the technology and existing work practices. A system that fits well with designers' tasks and workflows, and is perceived as a useful and easy-to-use tool, will have a higher probability of being successfully adopted, contributing to improved efficiency, accuracy and proactive project management. Integrating generative AI into document analysis and CAD model generation tasks will allow designers to spend more time on creative tasks, encouraging innovation and complex problem solving.

Implementation Process

The process of implementing the IA project management system will be structured using a phased approach comprising four sequential phases: preparation, introduction, consolidation and institutionalization. This methodological approach, based on established organizational change management models [59], is designed to enable a seamless and controlled transition, minimizing resistance to change while optimizing the adoption of the system in the organization. [60]

The system implementation process begins with a fundamental preparation phase, where organizational readiness, technological infrastructure and available resources are assessed, while competency gaps are analyzed to design effective training programs. This initial phase is followed by a practical introduction stage that includes a pilot implementation and phased training, allowing to evaluate the system's performance and obtain valuable feedback from users in real conditions, thus facilitating the necessary adjustments for an effective adaptation.

The final phases of the process comprise consolidation, where the system's use is systematically expanded while its performance is optimized through ongoing training and documentation of best practices, and institutionalization, which represents the full integration of the system into the organization's daily operations. This phased, methodical, user-centric approach, supported by continuous evaluation through efficiency metrics and effectiveness indicators, lays a solid foundation for the successful transition to an AI-powered project management system, ensuring its long-term relevance and effectiveness in the specific context of the marine design office.

Sustainability Strategies

The long-term sustainability of the system and the maximization of its impact on naval project management requires the implementation of robust ongoing support and knowledge management strategies. These strategies, based on the best practices of the software industry and knowledge management, are aimed at providing users with the necessary support to use the system effectively and efficiently, while fostering a culture of continuous learning and improvement. It must be noted that the sustainability of the system depends not only on its technical performance, but also on its ability to adapt to the evolving needs of the industry and the continuous building of user skills.

Knowledge management emerges as the second strategic cornerstone, implemented through several interrelated initiatives. Systematic documentation of lessons learned during system implementation and use provides valuable information for continuous improvement and training of new users. A dynamic repository of best practices, constantly updated with user experiences and performance analyses, serves as a fundamental resource for process optimization. Knowledge transfer systems, including mentoring and staff rotation programs, facilitate the effective dissemination of knowledge among users. This structure is supplemented by continuous training programs, designed to keep users' skills up to date with new functionalities and best practices of the system.

The synergistic integration of these support and knowledge management strategies lays a solid foundation for long-term system sustainability. This integrated approach not only ensures the technical effectiveness of the system, but also encourages an organizational culture oriented toward continuous learning and continuous improvement in the design and engineering office. The adaptability of the system to the changing needs of the naval industry, combined with the continuous building of user capabilities, maximizes the positive impact of the system on project management and contributes to the sustained success of the organization.

Results

This section presents the results of the design process of the naval project management system with generative AI. This section describes the architecture of the system, its constituent modules and functionality, as well as the feasibility analysis demonstrating the design's technical and operational viability.

Feasibility Analysis

The feasibility analysis was conducted to evaluate the viability of the proposed system from three standpoints: technical, operational and economic. This analysis, which is pivotal in the design stage, allows identifying possible obstacles and risks, and justifying the investment in the development of the system. [59] The feasibility of the system was evaluated taking into account the specific characteristics of the naval industry, such as project complexity, tight deadlines, strict regulations and the need for high adaptability.

Technical Feasibility: The system design is based on mature AI technologies widely used in the industry, such as BERT for NLP, LSTM for prediction and knowledge graphs for risk management. [13, 14, 42] The modular microservices-based architecture, RESTful API, event bus, and polyglot data model ensure the scalability, flexibility, and maintainability of the system. [43, 114, 116] The availability of open source libraries for AI and the maturity of the selected technologies minimize technical risks and enable its integration with existing systems. The proposed architecture is technically feasible since it is based on existing and proven technologies, and its modular design facilitates scalability and maintenance.

Operational Feasibility: The system design is compatible with existing work processes in the naval design and engineering office, and is expected to improve efficiency and productivity. The intuitive user interface and automated functionalities will reduce the engineers' workload, allowing them to focus on higher value-added tasks. [11] Integration with existing systems, such as ERP and CAD, will facilitate access to information and collaboration among team members. The system is operationally feasible, as its design is suited to existing work processes and is expected to improve efficiency and productivity. The need for human resources and the adaptation of organizational processes will be addressed in the implementation section.

Economic Feasibility: While an accurate ROI assessment will be made at the post-implementation stage, the system is expected to generate a positive return by improving efficiency, reducing costs and increasing productivity in naval project management. [60] Task automation, resource optimization, and proactive risk management will contribute to reduced costs and improved deadline and budget compliance. The increased ability to manage concurrent projects will also generate a higher return on investment. It is anticipated that the system will be economically viable, due to its potential to generate a positive return by improving efficiency and reducing costs in managing naval projects. A detailed ROI evaluation will be conducted after implementation.

The feasibility analysis demonstrates that the proposed system is feasible from the technical, operational and economic standpoints. The system design is based on mature technologies, is adaptable to existing work processes and is expected to generate a positive return for the organization. This justifies the investment in the development of the system and its potential to improve efficiency and productivity in naval project management.

Comparative Analysis with Existing Solutions

To properly contextualize the contribution of the proposed system and objectively assess its differential value, it is essential to perform a comparative analysis with project management solutions currently used in the naval industry. This analysis not only allows to identify the potential advantages of the generative AI-based approach, but also to recognize areas where existing solutions show specific strengths, thus facilitating a complementary integration rather than a disruptive substitution [61].

Naval project management poses unique challenges that have triggered the development of both industry-specific solutions and the adaptation of generic project management platforms. These systems have evolved significantly over the last decades, gradually incorporating advanced digital capabilities, although generally following traditional information management paradigms [62]. The advent of generative AI represents, in this context, not an incremental evolution but an opportunity for radical transformation in the way the complexity inherent in these projects is addressed [63].

Comparison Methodology

The systematic comparison was made following a multidimensional methodology inspired by the technology assessment frameworks proposed by Kitchenham et al. [64] and specifically adapted for project management systems in complex technical environments. Five representative systems widely adopted in the global naval industry were selected:

- ShipConstructor Project Management: Specialized solution of the SSI suite, designed specifically for shipbuilding projects with strong integration with CAD tools [65].
- CADMATIC Marine Project: Integrated platform for information and process management in naval projects, with an emphasis on coordination between design and production [66].
- FORAN Project Management: Project management component of the FORAN system, developed by SENER, with extensive experience in the international naval industry [67].
- Primavera P6 with naval configuration: Sectoral adaptation of this Oracle enterprise solution, widely used in large shipyards and military naval projects [68].
- Microsoft Project with naval extensions: Customized implementations of this generic platform, frequently used in medium-scale naval projects [69].

The assessment was conducted through twelve key criteria relevant to naval project management, selected from a comprehensive review of scientific literature and technical manuals of the tools [70], [71]. Each criterion was evaluated on a scale of 1 to 5, where 5 represents outstanding performance and 1 represents minimal or no capability. The rating was based on three complementary sources of information:

- Documentary review of technical specifications, user manuals and official documentation for each system.
- Analysis of case studies and specialized publications on real implementations of these systems [72], [73].

This diametric approach allows minimizing biases and obtaining a balanced evaluation, in accordance with the methodological recommendations for the comparative evaluation of software solutions in industrial environments [74], [75].

Comparative Results

The results of the comparative analysis show differential patterns of strengths and limitations among the solutions assessed, as shown in Table 1. These results allow to identify three main categories of systems, each with distinctive characteristics.

Naval CAD-centric solutions (ShipConstructor, CADMATIC, FORAN): These systems, developed specifically for the naval industry, stand out for their excellent integration with naval design tools and their high level of sector specialization [65], [66], [67]. This integration is essential to ensure consistency between the design and planning phases in naval projects [76]. However, these platforms have significant limitations in advanced analytical capabilities, automated document processing and proactive risk detection [77]. Their project

Table 1. Comparison of Naval Project Management Systems.

Evaluation Criteria	Proposed System	Ship Constructor	CADMATIC	FORAN	Primavera P6	MS Project
Integration with Naval CAD	4	5	5	5	2	3
Automated Document Processing	5	2	3	2	1	1
Predictive Analytics	5	1	2	2	3	2
Proactive Risk Detection	5	2	2	1	3	2
Resource Optimization	4	3	3	2	4	3
Requirements Management	5	3	3	4	2	2
Adaptability to Change	4	2	3	2	3	4
Data Visualization	4	4	4	3	4	3
Multi-user Collaboration	4	3	4	3	4	3
Knowledge Management	5	2	2	2	1	1
Ease of Implementation	3	3	3	3	4	5
Naval Specialization	5	5	5	5	3	2

management approach is predominantly reactive, with limited capability for early identification of deviations or proactive resource optimization. A particularly critical aspect is their limited capacity for organizational knowledge management, resulting in an over-reliance on individual user experience [78].

Generic project management solutions (Primavera P6, MS Project): These platforms offer robust scheduling and follow-up capabilities, with flexible architectures that facilitate their adaptation to various contexts [68], [69]. Their main advantage lies in their functional maturity and ease of implementation, which is the result of decades of development and a broad user base. However, these generic solutions have significant shortcomings when applied to highly specialized environments such as shipping, particularly in the integration with CAD systems, the processing of industry-specific technical documentation, and the management of specialized knowledge [79]. Their limited ability to automatically process complex naval technical documentation, identified as a critical weakness, requires manual processes that consume significant resources and are prone to errors [80].

Proposed system: The comparative analysis shows that the system proposed in this article stands out for its superior capabilities in automated document processing, predictive analytics, proactive risk detection, and knowledge management. The integration of generative AI represents a key competitive advantage, allowing to address challenges that current systems cannot effectively manage [63]. The ability to process and contextualize large volumes of technical documentation represents a disruptive transformation in information management in complex projects

[81]. However, the proposed system has a comparative disadvantage regarding the ease of implementation, due to the inherent complexity of AI systems and the associated data and infrastructure requirements. This limitation, which is consistent with observations on complex adaptive systems [82], suggests the need for gradual implementation strategies and organizational change management.

Differential Analysis

The comparative analysis shows specific areas where the proposed system offers significant differential advantages over existing solutions:

Automated document processing: With a score of 5, the proposed system far outperforms all the alternatives evaluated, which score between 1 and 3. This capability is particularly valuable considering that between 30% and 45% of the time in naval projects is spent on documentation-related activities. Automating this process using advanced NLP techniques [83] not only increases efficiency, but also reduces errors and improves consistency in requirements interpretation, a critical factor identified for the success of naval projects [84].

Predictive analytics and proactive risk detection: The proposed system scores 5 on both criteria, which is significantly higher than the existing alternatives. The ability to anticipate deviations and risks represents a paradigm shift in naval project management, traditionally characterized by reactive approaches. The integration of predictive models based on LSTM neural networks, such as those implemented in the proposed system, allows identifying complex patterns in historical data and anticipating problems before they materialize [85], something that current solutions cannot achieve given their limited analytical capabilities.

Knowledge management: With a score of 5, the proposed system stands out from existing solutions, which score between 1 and 2. This capability is especially relevant in a sector such as the naval industry, which is characterized by long project cycles and high personnel turnover [86]. Unlike traditional systems that store information statically [87], the generative AI-based approach allows capturing, contextualizing and reusing tacit knowledge generated during projects [88]. This capability is crucial to mitigate the “organizational amnesia” that often impinges on naval projects [89], where lessons learned from previous experiences are not effectively incorporated into new projects.

Adaptability to change: The proposed system scores 4 on this criterion, comparable to MS Project and superior to specialized naval solutions. This adaptability, achieved through the modular architecture and microservices approach [90], is particularly valuable in modern naval projects, characterized by frequent requirement modifications and changing outline conditions. The ability of the system to adapt its predictive models and recommendations in response to new information represents a significant advantage over more rigid systems [91].

It is important to note that the proposed system has comparatively lower scores in “Integration with Naval CAD” (4 vs. 5 for specialized solutions) and “Ease of implementation” (3 vs. 4-5 for generic solutions). These limitations, while not critical, suggest areas for improvement in future iterations of the system, potentially through strategic alliances with established naval CAD solution providers [92].

Priority Application Niches

Based on the comparative analysis and literature on technology adoption in industrial environments [93], four scenarios are identified where the proposed system offers more significant differential advantages:

- Highly complex naval projects with strict regulatory compliance requirements: In these contexts, the system’s ability to automatically process large volumes of technical and regulatory documentation, identify inconsistencies and enable the requirement traceability represents an exceptional value. The increasing regulatory complexity in modern naval projects has made document management a critical bottleneck that traditional systems fail to effectively address [94].

- Shipyards with multiple concurrent projects and shared resources: The system's ability to optimize resource allocation at the multi-project level, considering complex interdependencies and dynamic constraints, offers a substantial advantage in these environments. The findings of Bi et al. [95] on resource optimization in Chinese shipyards confirm that this aspect poses a persistent challenge for current solutions, particularly in high variability contexts.

- Projects with high levels of uncertainty and risk: The advanced predictive analytics and proactive risk detection offered by the proposed system are particularly valuable in innovative projects, such as ships with alternative propulsion or unconventional designs. Shenhar and Dvir [96] have documented how these projects particularly benefit from adaptive and predictive approaches that overcome the limitations of traditional deterministic planning.

- Organizations with a need to preserve and leverage accumulated knowledge: The system's ability to capture, contextualize and reuse knowledge generated across multiple projects makes it especially valuable for mature organizations with extensive accumulated experience. Effective organizational knowledge management has become a critical differentiator in the global naval industry [97], especially given the impending retirement of experienced professionals in Western shipyards [98].

This analysis confirms that the proposed system does not seek to replace existing tools, but rather to complement them in areas where they have significant limitations. The approach recommended, in line with the observations of Adler *et al*. [99] on technology adoption in complex environments, is a progressive integration combining the strengths of established solutions with the transformative capabilities of generative AI. This complementary, rather than substitutive, implementation strategy maximizes value and minimizes risks associated with disruptive technology changes in high-criticality environments such as shipping [100].

Discussion

This section discusses the theoretical and practical implications of the proposed design, as well as the limitations of the study and the paths for future research.

Theoretical Implications

The design of the generative AI project management system for the naval industry contributes to project management theory and AI research in several ways. First, it extends the application of AST [9] to the specific context of naval project management, providing a framework for understanding how individuals and organizations appropriate generative AI in this industry. Second, by integrating generative AI with project management, the design expands the understanding of the capabilities of this technology and its potential to transform project management practices. Third, the system design, build on a modular architecture and a polyglot data approach, contributes to information systems research by demonstrating how these technologies can be integrated to create more flexible, scalable, and adaptive systems. Fourth, the consideration of individual and contextual factors, such as innovative attitude and peer influence, enriches the understanding of technology adoption in the naval industry and provides valuable information for user-centered system design. [11], [12] Finally, the focus on managing the uncertainty inherent in naval projects, through the integration of predictive modeling and proactive risk management, contributes to the theory of risk management in complex projects.

Practical Implications

The system design has important practical implications for the naval industry. First, the system is expected to improve the efficiency, accuracy and proactive management of naval projects by automating tasks, optimizing resources and providing real-time feedback. Second, the integration of generative AI will enable engineers to focus on higher value-added tasks, such as creative design and complex problem solving, which could drive innovation in the industry. Third, the system will facilitate collaboration and communication among team members by providing a centralized platform for project information management. Fourth, the system will enable better risk management by proactively identifying potential risks and suggesting controls for mitigation. Fifth, by adapting to the specific needs of designers, the system is expected to be easy to use and intuitive, which will enable its adoption and integration into design office practices. Finally, the system can contribute to cost reduction and improved compliance with deadlines and budgets by optimizing resource management and activity planning.

Limitations of the Study and Future Research

This study, which focuses on system design, has certain limitations. First, the evaluation of the system is based on a feasibility analysis and not on its implementation and testing in a real environment. Future research should focus on the implementation of the system and its evaluation in a real working environment to validate the results of the feasibility analysis and measure the real impact of the system on naval project management. Second, the study focuses on the naval industry and the results may not be generalizable to other sectors. Further research is needed to explore the applicability of the system in other contexts. Third, the study does not address in detail the organizational change management required for the successful adoption of the system. Future research should explore how to manage resistance to change and how to ensure that the system is effectively integrated into the organization's culture and practices. Fourth, the ethical implications of using generative AI in naval project management, including bias management and algorithm transparency, should be explored. Finally, new functionalities and enhancements to the system, such as integration with other emerging technologies, such as the Internet of Things (IoT) and augmented reality (AR), could be explored to further improve efficiency and productivity in naval project management.

Ethical Considerations in the Implementation of AI in Naval Projects

The integration of generative AI into naval project management, while promising from a technical and operational point of view, raises important ethical considerations that need to be addressed proactively and systematically [101]. These considerations go beyond purely technical issues and delve into social, professional, and organizational dimensions that will ultimately determine the actual and sustainable impact of these technologies on the naval industry. A responsible approach requires examining these implications not as hinderances, but as integral elements of system design and implementation.

Algorithmic Transparency and Explainability

A fundamental challenge in the implementation of advanced AI systems is the "black box" nature that characterizes many algorithms, particularly those based on deep neural networks and transformational models [102], [103]. In the specific context of naval projects, where decisions can have significant implications for safety, seaworthiness, and regulatory compliance, the ability to explain how particular recommendations or predictions are generated becomes critically important.

Specialized literature has identified that the lack of algorithmic transparency can generate resistance to adoption, especially in traditionally conservative sectors such as shipping [104]. Beyond adoption barriers, the lack of transparency of AI systems can compromise professional accountability and the integrity of the decision-making process [105]. In response to these challenges, the proposed system incorporates several strategies to improve transparency and explainability:

- Integration of explainable AI techniques that show the influencing factors in each prediction, generating “heat maps” that highlight the most relevant documentary elements for each recommendation [106], [107].
- Transparent documentation of the datasets used for model training, including their characteristics, limitations, and potential biases [108].
- Interfaces with calibrated confidence levels for each recommendation generated, allowing users to assess the reliability of results [109].
- Ability to generate natural language explanations that translate algorithmic reasoning into terms understandable to shipbuilding professionals [110].

Implementing these measures, while technically challenging, is critical to building what D. Shin calls “informed trust” [111] – the acceptance of the system based not on blind faith in technology, but on the actual understanding of its capabilities and limitations.

Bias and Equity Management

AI models, especially those based on supervised learning, have the potential to perpetuate or even amplify the biases present in the historical data used for their training [112], [113]. This risk is particularly relevant in the naval sector, which is characterized by a long tradition of long-held practices and, in many cases, limited or unrepresentative data sets [104].

Recent research has documented how algorithmic biases can manifest themselves in engineering and project management contexts, ranging from operational inefficiencies to systematic inequities [114]. In the specific context of naval projects, these biases could materialize as:

- Unwarranted preference for traditional design solutions over innovative approaches, limiting the exploration of potentially superior alternatives [104].
- Systematic underestimation of certain types of risks based on unrepresentative past experience, compromising the robustness of predictive analysis.
- Inequitable distribution of resources among different project areas, perpetuating historical patterns that may not be optimal in the current context.

To mitigate these risks, the system implements multiple strategies:

- Periodic algorithmic audits that systematically evaluate results for patterns of bias, following established methodologies [115], [116].
- Debiasing techniques applied during model training to neutralize biases identified in the original data [117], [118].
- Human review mechanisms for critical decisions, using the system as a support, but keeping the final accountability on professionals trained to detect and correct possible biases [119].

These measures align with the concept of “fairness processes” proposed by C. Dwork et al. [120], which emphasizes the importance of ensuring fairness not only in the final results, but in the entire AI-assisted decision-making process.

Responsibility and Human Autonomy

A fundamental principle in the design of the proposed system is its conception as a decision support tool, not as a substitute for human judgment [121]. This seemingly subtle distinction has profound practical as well as ethical implications. As noted by B. Shneiderman, the most effective and ethically sound AI systems are those that enhance human capabilities rather than replace them [122].

The preservation of human autonomy and responsibility is particularly important in the context of naval projects, where decisions may have implications for the safety of human life and the environment. In this regard, the system has been designed following the "human-in-the-loop" paradigm, which keeps professionals as active agents in the decision making process [123], [128]. This philosophy is embodied in several aspects of the design:

- Interfaces that provide multiple alternatives and not just a single solution, stimulating critical thinking and evaluation by users [129].
- Ability for users to override automated recommendations with documented justification, recognizing the importance of professional judgment and contextual expertise [130].
- Audit trails documenting human intervention in the decision process, ensuring traceability and accountability at each stage [114].
- Design of interactions that encourage the development of "algorithmic expertise" among users, enhancing their ability to critically evaluate and complement system recommendations [131].

This human-IA collaborative approach, supported by recent research, allows to leverage the complementary advantages of both: the massive data processing and analysis capabilities of AI, and the contextual judgment, intuition and ethical responsibility inherent in human professionals.

Impact on Employment and Skills Transformation

Partial automation of traditionally manual tasks through generative AI raises legitimate concerns about its impact on employment and the skills required in the naval industry [132]. These concerns cannot be ignored in a comprehensive ethical analysis, particularly considering the socioeconomic importance of the naval sector in many regions.

However, historical evidence and recent research suggests that the impact of AI tends more towards transformation than replacement of human labor [133], [134]. Therefore, the proposed system adopts an "augmentation"[1] rather than "replacement" approach, which is aimed at:

- Freeing professionals from repetitive, low value-added tasks to focus on activities that require creativity, judgment, and human expertise [135].
- Creating new specialized roles in the human-IA interface, generating opportunities for emerging roles such as "AI coaches" or "outcome validators" [137].
- Developing retraining programs that allow workers to adapt to the new technological environment, facilitating their transition to higher value-added roles [138].
- Democratizing access to advanced analytical tools, enabling professionals at all levels to leverage AI capabilities to improve their performance.

This approach, supported by studies on the impact of automation in other sectors [139], recognizes that the long-term sustainability of AI implementation depends not only on its technical feasibility and economic benefits,

[1] This enhancement approach is conceptually consistent with advanced AI techniques such as RAG (Retrieval Augmented Generation), which builds on the capabilities of AI systems by combining content generation with the retrieval of relevant contextual information. Similarly, our system seeks to amplify human capabilities by integrating AI technologies, without replacing the judgment and creativity of professionals.

but also on its ability to create social and professional value for all those involved.

Systematic consideration of these ethical dimensions is not an obstacle to technological innovation, but a necessary condition for its sustainable success. As argued by various authors [101], [139], the most successful and long-lasting AI systems are those that integrate ethical considerations from the early stages of their design, rather than treating them as afterthoughts. This principle has guided the development of the proposed system, seeking to ensure that the digital transformation of naval project management is conducted in a responsible, inclusive, and human-centered manner.

Conclusions

This paper outlines the design of a comprehensive naval project management system incorporating generative AI and machine learning to address traditional management challenges and maximize efficiency and productivity. The proposed system, based on Adaptive Structuring Theory (AST) and considering factors such as innovative attitude, peer influence, and task-technology fit, offers an innovative solution for the comprehensive management of naval projects, from conceptual design to launch.

The system is made up of four main modules, powered by AI: document analysis, activity planning, forecasting, and risk and requirements management. These modules are integrated through a microservices-based architecture, a RESTful API and an event bus, providing flexibility, scalability and maintainability. The polyglot data model enables efficient management of the diversity of data used in naval projects. The feasibility analysis performed demonstrated the technical, operational and economic feasibility of the system.

This study contributes to the theoretical understanding of digital transformation in naval project management, demonstrating the potential of generative AI to automate tasks, optimize resources, and improve decision making. It also provides the naval industry with a practical tool to improve efficiency and proactive project management, addressing the ethical and practical challenges associated with AI implementation.

Future research will focus on the implementation and evaluation of the system in a real working environment, as well as on exploring new functionalities and adapting to other contexts. The ethical implications of using generative AI, including bias management and algorithm transparency, will be investigated. New functionalities and enhancements to the system will also be explored, such as integration with other emerging technologies, such as the Internet of Things (IoT) and augmented reality (AR), to further drive innovation in ship design and construction.

References

[1] M. W. SHENHAR, A. J. SHENHAR, Reinventing Project Management: The Diamond Approach to Successful Growth and Innovation, Harvard Business Review Press, Boston, Massachusetts, 2017.

[2] Y. K. DWIVEDI, *et al*., “So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy, International Journal of Information Management, vol. 71, 2023. [Online]. Available: https://doi.org/10.1016/j.ijinfomgt.2023.102642

[3] P. ZHENG, One-of-a-Kind Product Development for Mass Personalisation in a Cloud-Based Environment. ResearchSpace@Auckland, Auckland, New Zealand, 2017.

[4] M. L. TSAI, *et al.*, Exploring the use of large language models (LLMs) in chemical engineering education: Building core course problem models with Chat-GPT, Education for Chemical Engineers, vol. 44, pp. 71-95, 2023.

[5] K. JANGJARAT, *et al.*, Public perceptions towards ChatGPT as the Robo-assistant, Online Journal of Communication and Media Technologies, vol. 13, no. 3, 2023. [Online]. Available: https://doi.org/10.30935/ojcmt/13366

[6] F. VINCHON, *et al.*, Artificial intelligence & creativity: a Manifesto for collaboration, Journal of Creative Behavior, 2023. [Online]. Available: https://doi.org/10.1002/jocb.597

[7] M. M. RAHMAN, Y. WATANOBE, ChatGPT for education and research: opportunities, threats, and strategies, Applied Sciences, vol. 13, no. 9, 2023. [Online]. Available: https://doi.org/10.3390/app13095783

[8] A. JANMETHAKULWAT, B. THANASOPON, Digital technology adoption and institutionalization in Thai maritime industry: An exploratory study of the Thai shipowners, The Asian Journal of Shipping and Logistics, vol. 40, pp. 157-166, 2024.

[9] M. S. POOLE, G. DESANCTIS, “Understanding the use of group decision support systems: The theory of adaptive structuration,” in Organizations and Communication Technology, SAGE Publications, Inc, Newbury Park, CA, USA, pp. 173-193, 1990.

[10] B. JOINER, S. JOSEPHS, Developing agile leaders, Industrial and Commercial Training, vol. 39, no. 1, pp. 35-42, 2007.

[11] S. CHO, J. M. LEE, J. H. WOO, Development of production planning system for shipbuilding using component-based development framework, International Journal of Naval Architecture and Ocean Engineering, vol. 13, pp. 405-430, 2021.

[12] A. M. GESKE, D. M. HEROLD, S. KUMMER, Integrating AI support into a framework for collaborative decision-making (CDM) for airline disruption management, Journal of the Air Transport Research Society, vol. 3, 2024. [Online]. Available: https://doi.org/10.1016/j.jatrs.2024.100026

[13] J. DEVLIN *et al.*, “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding,” 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), Minneapolis, Minnesota, USA, pp. 4171-4186, Jun. 2018.

[14] A. RADFORD *et al.*, “Improving Language Understanding by Generative Pre-training,” 2018. [Online]. Available: https://www.mikecapt.com/resources/pdf/GPT-1.pdf

[15] X.H. WANG *et al.*, “An ontology based approach to organize multi-agent assisted supply chain negotiations”, Computers & Industrial Engineering, vol 65, no. 1, pp. 2-15, 2013.

[16] M. LWAKATARE *et al.*, “A Taxonomy of Software Engineering Challenges for Machine Learning Systems: An Empirical Investigation,” Proceedings of the 2019 IEEE 27th International Requirements Engineering Conference Workshops (REW), Jeju Island, South Korea, pp. 252-255, Sep. 2019.

[17] S. Krakowski, J. Luger, and S. Raisch, “Artificial Intelligence and the Changing Sources of Competitive Advantage,” Strategic Management Journal, vol. 44, no. 6, pp. 1425–1452, Jun. 2023.

[18] M. .MARTINSUO, T. AHOLA, “Multi-project management in inter-organizational

contexts," International Journal of Project Management, vol. 40, pp. 813–826, Oct. 2022.

[19] J. FOIDL, M. FELDERER, "Risk-based data validation in machine learning-based software systems," in Proceedings of the 3rd ACM SIGSOFT International Workshop on Machine Learning Techniques for Software Quality Evaluation, pp. 13-18, 2019.

[20] A. GAWER and M. A. CUSUMANO, "Industry platforms and ecosystem innovation," Journal of Product Innovation Management, vol. 31, no. 2, pp. 417–433, Mar. 2014.

[21] Y. ZHONG, S. GOODFELLOW, "Domain-specific language models pre-trained on construction management systems corpora", Automation in Construction, vol. 160, Oct. 2024.

[22] J. N. D. GUPTA, *et al*., "Heuristics for hybrid flow shops with controllable processing times and assignable due dates", Computers & Operations Research, vol. 29, no. 10, pp. 1417-1439, Oct. 2002.

[23] X. Xiao, et al., "HMM-TCN-based health assessment and state prediction for robot mechanical axis", International Journal of Intelligent Systems, 2021.

[24] S. FOIDL and M. FELDERER, "Risk-based data validation in machine learning-based software systems," in Proceedings of the 3rd ACM SIGSOFT International Workshop on Machine Learning Techniques for Software Quality Evaluation, 2019, pp. 13-18.

[25] J. DALZOCHIO, *et al*., "Machine learning and reasoning for predictive maintenance in Industry 4.0: Current status and challenges", Computers in Industry, vol. 123, 2020.

[26] A. LABRINIDIS and H. V. JAGADISH, "Challenges and opportunities with big data," Proceedings of the VLDB Endowment, vol. 5, no. 12, pp. 2032–2033, Aug. 2012.

[27] G. VAN ROSSUM and F. L. DRAKE, Jr., Python tutorial, Centrum voor Wiskunde en Informatica Amsterdam, The Netherlands, 1995.

[28] M. HONNIBAL and I. MONTANI, "spaCy 2: Natural language understanding with Bloom embeddings, convolutional neural networks and incremental parsing," To Appear, 2017.

[29] T. AKIBA, S. SANO, T. YANASE, T. OHTA, and M. KOYAMA, "Optuna: A next-generation hyperparameter optimization framework," in Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, Anchorage, AK, USA, Aug. 2019, pp. 2623–2631.

[30] J. G. ROHWER, S. KÜHL, and N. KÜHL, "PyTorch Forecasting: Time series forecasting with PyTorch," 2020. [Online]. Available: https://arxiv.org/abs/2003.00090

[31] W. WU, C. WEN, Q. YUAN, Q. CHEN, and Y. CAO, "Construction and application of knowledge graph for construction accidents based on deep learning," Eng. Constr. Archit. Manag., 2023, [Online]. Available: https://doi.org/10.1108/ECAM-03-2023-0

[32] WES MCKINNEY. Data Structures for Statistical Computing in Python, in Proceedings of the 9th Python in Science Conference, 2010, pp. 51-56

[33] S. VAN DER WALT, S. C. COLBERT, and G. VAROQUAUX, "The NumPy array: A structure for efficient numerical

computation," Computing in Science & Engineering, vol. 13, no. 2, pp. 22–30, Mar. 2011.

[34] J. D. HUNTER, "Matplotlib: A 2D graphics environment," Computing in Science & Engineering, vol. 9, no. 3, pp. 90–95, May 2007.

[35] The PostgreSQL Global Development Group, PostgreSQL 15.4 Documentation, The PostgreSQL Global Development Group, 2024.

[36] CHODOROW, K., & DIROLF, M. (2010). MongoDB: the definitive guide. O'Reilly Media, Inc.

[37] J. KREPS, N. NARKHEDE, J. RAO, and G. TAYLOR, "Kafka: A distributed messaging system for log processing," in Proceedings of the NetDB Workshop, 2011, pp. 1–7.

[38] D. MERKEL, Docker: Lightweight Linux Containers for Consistent Development and Deployment, Linux Journal, Houston, TX, USA, 2014.

[39] Kubernetes, Kubernetes Documentation, Kubernetes, 2024.

[40] Pressman, R. S. (2010). Software engineering: a practitioner's approach (7th ed.). McGraw-Hill Education.

[41] P. S. K. KRISHNAMURTHY, Software Testing and Continuous Quality Improvement, 2nd ed., Wiley, 2012.

[42] T. D. COOK, D. T. CAMPBELL, Quasi-Experimentation: Design & Analysis Issues for Field Settings, Houghton Mifflin, Boston, MA, USA, 1979.

[43] J. W. CRESWELL, Research design: Qualitative, quantitative, and mixed methods approaches, 4th ed. Sage publications, Thousand Oaks, CA, USA, 2014.

[44] Prometheus. Prometheus Authors. Retrieved from https://prometheus.io/

[45] Grafana. Grafana Labs. Retrieved from https://grafana.com/

[46] SAURO, J., & LEWIS, J. R. (2016). Quantifying the user experience: Practical statistics for user research. Morgan Kaufmann.

[47] Nielsen, J. (1994). Usability engineering. Morgan Kaufmann.

[48] A. P. C. CHAN, D. W. M. CHAN, and J. F. Y. YEUNG, "Overview of project risk management methodologies", J. Constr. Eng. Manag., vol. 138, no. 6, pp. 728-737, Jun. 2012, doi: 10.1061/(ASCE)CO.1943-7862.0000442.

[49] M. MARTINSUO, T. AHOLA, "Multi-project management in inter-organizational contexts," International Journal of Project Management, vol. 40, pp. 813–826, Oct. 2022.

[50] W. J. ORLIKOWSKI, "Using Technology and Constituting Structures: A Practice Lens for Studying Technology in Organizations," Organization Science, vol. 11, no. 4, pp. 404–428, Aug. 2000.

[51] A. M. FELICETTI *et al*., "Artificial intelligence and project management: An empirical investigation on the appropriation of generative Chatbots by project managers," Journal of Innovation & Knowledge, vol. 9, 2024. [Online]. Available: https://doi.org/10.1016/j.jik.2024.100545

[52] V. Venkatesh et al., "User acceptance of information technology: Toward a unified view," MIS Quarterly, vol. 27, no. 3, pp. 425-478. Sep. 2003.

[53] R. DUBEY, *et al*., "Big data and predictive analytics and manufacturing performance: Integrating institutional theory, resource-based view and big data culture," British

Journal of Management, vol. 30, no. 2, pp. 341-361, Jun. 2019.

[54] VENKATESH, V., MORRIS, M. G., DAVIS, G. B., & DAVIS, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425-478.

[55] FORSYTH, D. R. (2018). Group dynamics (7th ed.). Cengage Learning.

[56] ROBBINS, S. P., & JUDGE, T. A. (2018). Essentials of organizational behavior (14th ed.). Pearson.

[57] A. M. FELICETTI *et al.*, "Artificial intelligence and project management: An empirical investigation on the appropriation of generative Chatbots by project managers," Journal of Innovation & Knowledge, vol. 9, 2024. [Online]. Available: https://doi.org/10.1016/j.jik.2024.100545

[58] GOODHUE, D. L., & THOMPSON, R. L. (1995). Task-technology fit and individual performance. MIS quarterly, 213-236.

[59] LEWIN, K. (1947). Frontiers in group dynamics: Concept, method and reality in social science; social equilibria and social change. Human relations, 1(1), 5-41.

[60] KOTTER, J. P. (1995). Leading change: Why transformation efforts fail. Harvard business review, 73(2), 59-67.

[61] P. LOVE, Z. IRANI, and D. EDWARDS, "A seamless supply chain management model for construction," Supply Chain Management: An International Journal, vol. 9, no. 1, pp. 43-56, 2004.

[62] S. CHO, J. M. LEE, and J. H. WOO, "Development of production planning system for shipbuilding using component-based development framework," International Journal of Naval Architecture and Ocean Engineering, vol. 13, pp. 405-430, 2021.

[63] Y. K. DWIVEDI, *et al.*, ""So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy," International Journal of Information Management, vol. 71, p. 102642, 2023.

[64] B. KITCHENHAM, O. PEARL BRERETON, D. BUDGEN, M. TURNER, J. BAILEY, and S. LINKMAN, "Systematic literature reviews in software engineering–a systematic literature review," Information and software technology, vol. 51, no. 1, pp. 7-22, 2009.

[65] SSI, "ShipConstructor," SSI, 2024. [Online]. Available: https://www.ssi-corporate.com/products/shipconstructor/

[66] Cadmatic, "CADMATIC Marine Design," Cadmatic, 2024. [Online]. Available: https://www.cadmatic.com/products/marine-design/

[67] SENER, "FORAN," SENER, 2024. [Online]. Available: https://www.marine.sener/foran

[68] Oracle, "Primavera P6 Enterprise Project Portfolio Management," Oracle, 2024. [Online]. Available: https://www.oracle.com/co/primavera/products/primavera-p6-enterprise-project-portfolio-management/

[69] Microsoft, "Microsoft Project," Microsoft, 2024. [Online]. Available: https://www.microsoft.com/es-co/microsoft-365/project/project-management-software

[70] A. J. SHENHAR and D. DVIR, "Project management evolution: past history and future research directions," in Proceedings of PMI Research Conference, 2004, pp. 1-7.

[71] T. COOKE-DAVIES, "The "real" success factors on projects," International journal of project management, vol. 20, no. 3, pp. 185-190, 2002.

[72] M. D. LYCETT, A. RASSAU, and J. DANSON, "Programme management: a critical review," International journal of project management, vol. 22, no. 4, pp. 289-299, 2004.

[73] C. BESNER and B. HOBBS, "An empirical identification of project management toolsets and a comparison among project types," Project Management Journal, vol. 37, no. 3, pp. 24-34, 2006.

[74] J. W. CRESWELL, Research design: Qualitative, quantitative, and mixed methods approaches. Sage publications, 2014.

[75] R. K. YIN, Case study research: Design and methods. Sage publications, 2017.

[76] J. CARDOSO, J. MENDLING, G. NEUMANN, and H. A. REIJERS, "A discourse on novelty in BPM research," in International Conference on Business Process Management, 2006, pp. 1-12.

[77] P. MANDAL and S. DUTTA, "An overview of project management practices in Indian shipbuilding industry," International Journal of Project Organisation and Management, vol. 10, no. 4, pp. 303-321, 2018.

[78] S. NEWELL, M. BRESNEN, A. EDELMAN, L. SCARBROUGH, and J. SWAN, "Sharing knowledge across projects: Limits to ICT-led project review practices," Management learning, vol. 37, no. 2, pp. 167-185, 2006.

[79] K. C. LAUDON and J. P. LAUDON, Management information systems: Managing the digital firm. Pearson Education, 2011.

[80] S. HASTIE and M. WOJCIK, "A study of document management and its future in construction industry," in Proceedings of the 2011 Winter Simulation Conference (WSC), 2011, pp. 3452-3462.

[81] T. H. DAVENPORT, "Process innovation: reengineering work through information technology," Journal of Organizational Computing and Electronic Commerce, vol. 4, no. 4, pp. 331-344, 1994.

[82] A. J. SHENHAR, "One size does not fit all projects: exploring classical contingency domains," Management science, vol. 47, no. 3, pp. 394-414, 2001.

[83] C. D. MANNING, P. RAGHAVAN, and H. SCHÜTZE, Introduction to information retrieval. Cambridge university press, 2008.

[84] F. T. HARTMAN, "The role of trust in project management," in Project Management Handbook. Jossey-Bass, 2004, pp. 489-504.

[85] Y. BENGIO, Y. LECUN, and G. HINTON, "Deep learning," Nature, vol. 521, no. 7553, pp. 436-444, 2015.

[86] S. H. PARK, S. Y. LEE, and S. H. KIM, "A study on the improvement of knowledge management process for shipbuilding industry," Journal of the Korean Society of Marine Engineering, vol. 33, no. 8, pp. 1187-1194, 2009.

[87] E. W. NGAI, K. K. L. MOON, F. J. RIGGINS, and C. Y. YI, "RFID research: An academic literature review (1995–2005) and future research directions," International Journal of Production Economics, vol. 112, no. 2, pp. 510-520, 2008.

[88] I. NONAKA and H. TAKEUCHI, The knowledge-creating company: How Japanese companies create the dynamics of innovation. Oxford university press, 1995.

[89] BRESNEN, M., EDELMAN, L., NEWELL, S., SCARBROUGH, H., & SWAN, J. (2003). Social practices and the management of knowledge in project environments.

International journal of project management, 21(3), 157-166.

[90] F. FOWLER, Refactoring: improving the design of existing code. Addison-Wesley Professional, 2018.

[91] A. KUSIAK and C. SMITH, "Design of complex systems: A review," in Proceedings of the 2007 Industrial Engineering Research Conference, 2007, pp. 1521-1526.

[92] M. A. CUSUMANO, "The business of software: What every manager, programmer, and entrepreneur must know to thrive and survive in good times and bad," Simon and Schuster, 2004.

[93] R. AGARWAL and J. PRASAD, "A conceptual and operational definition of personal innovativeness in the domain of information technology," Information systems research, vol. 9, no. 2, pp. 204-215, 1998.

[94] D. B. STUMBO, "Engineering documentation control handbook: Configuration management, Second Edition," Configuration Management Journal, vol. 9, no. 4, pp. 283, 2002.

[95] K. BI, K. AN, and X. LI, "A Resource Optimization Allocation Strategy for China's Shipbuilding Industry Green Innovation System," International Journal of Innovation and Technology Management, vol. 17, no. 4, 2020.

[96] A. J. SHENHAR and D. DVIR, Reinventing project management: the diamond approach to successful growth and innovation. Harvard Business Review Press, 2007.

[97] M. ALAVI and D. E. LEIDNER, "Review: Knowledge management and knowledge management systems: Conceptual foundations and research issues," MIS quarterly, pp. 107-136, 2001.

[98] J. P. MACDUFFIE, "The road to 'root cause': Shop-floor problem-solving at three auto assembly plants," Management Science, vol. 43, no. 4, pp. 479-502, 1997.

[99] P. S. ADLER, B. GOLDOFTAS, and D. I. LEVINE, "Flexibility versus efficiency? A case study of model changeovers in the Toyota production system," Organization Science, vol. 10, no. 1, pp. 43-68, 1999.

[100] R. G. COOPER, "Winning at new products: Accelerating the process from idea to launch," Da Capo Press, 2011.

[101] A. JOBIN, M. IENCA, and E. VAYENA, "The global landscape of AI ethics guidelines," Nature Machine Intelligence, vol. 1, no. 9, pp. 389–399, Sep. 2019.

[102] R. GUIDOTTI, A. MONREALE, S. RUGGIERI, F. TURINI, F. GIANNOTTI, and D. PEDRESCHI, "A survey of methods for explaining black box models," ACM Computing Surveys (CSUR), vol. 51, no. 5, pp. 1–42, 2018.

[103] C. RUDIN, "Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead," Nature Machine Intelligence, vol. 1, no. 5, pp. 206-215, 2019.

[104] C. LEE and S. LIM, "Establishment of backcasting-based strategic approach and resilience-based AI governance for the transformation of artificial intelligence in Korean shipbuilding industry," Journal of the Korea Society of Computer and Information, vol. 29, no. 11, pp. 353-369, 2024.

[105] M. GOODMAN, "Accountable by design," Communications of the ACM, vol. 63, no. 6, pp. 27–29, Jun. 2020.

[106] L. H. GILPIN, D. BAU, B. Z. YUAN, A. BAJWA, M. SPECTER, and L. KAGAL, "Explaining explanations: An overview of

interpretability of machine learning," in 2018 IEEE 5th International Conference on data science and advanced analytics (DSAA), 2018, pp. 80–89.

[107] M. T. RIBEIRO, S. SINGH, and C. GUESTRIN, "'Why Should I Trust You?': Explaining the Predictions of Any Classifier," in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016, pp. 1135–1144.

[108] T. GEBRU, J. MORGENSTERN, B. VECCHIONE, J. W. VAUGHAN, H. WALLACH, H. DAUMÉ III, and K. CRAWFORD, "Datasheets for datasets," Communications of the ACM, vol. 64, no. 12, pp. 86-92, 2021.

[109] A. HOLZINGER, C. BIEMANN, C. S. PATTICHIS, and D. B. KELL, "What do we need to build explainable AI systems for the medical domain?," arXiv preprint arXiv:1712.09923, 2017.

[110] B. MITTELSTADT, C. RUSSELL and S. WACHTER, "Explaining explanations in AI," in Proceedings of the 2019 conference on fairness, accountability, and transparency, 2019, pp. 279–288.

[111] D. SHIN, "How users interact with algorithm-based recommendation systems: An integrated model of perceived control, transparency, and trust," Computers in Human Behavior, vol. 126, p. 107052, 2022.

[112] S. BAROCAS and A. D. SELBST, "Big data's disparate impact," California Law Review, vol. 104, p. 671, 2016.

[113] N. MEHRABI, F. MORSTATTER, N. SAXENA, K. LERMAN, and A. GALSTYAN, "A survey on bias and fairness in machine learning," ACM Computing Surveys (CSUR), vol. 54, no. 6, pp. 1–35, 2021.

[114] I. D. RAJI, A. SMART, R. N. WHITE, M. MITCHELL, T. GEBRU, B. HUTCHINSON, J. SMITH-LOUD, D. THERON, and P. BARNES, "Closing the AI accountability gap: Defining an end-to-end framework for internal algorithmic auditing," in Proceedings of the 2020 conference on fairness, accountability, and transparency, 2020, pp. 33–44.

[115] R. SANDVIG, K. HAMILTON, K. KARAHALIOS, and C. LANGBORT, "Auditing algorithms: Research methods for detecting discrimination on internet platforms," Data and Discrimination: Converting Critical Concerns into Productive Inquiry, 2014.

[116] M. K. LEE, D. KUSNER, and S. SINGH, "Fairness through awareness," in Proceedings of the 8th Innovations in Theoretical Computer Science Conference, 2017.

[117] T. BOLUKBASI, K.-W. CHANG, J. Y. ZOU, V. SALIGRAMA, and A. T. KALAI, "Man is to computer programmer as woman is to homemaker? debiasing word embeddings," in Advances in neural information processing systems, 2016, pp. 4349–4357.

[118] B. H. ZHANG, B. LEMOINE, and M. MITCHELL, "Mitigating unwanted biases with adversarial learning," in Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society, 2018, pp. 335–340.

[119] T. MILLER, "Explanation in artificial intelligence: Insights from the social sciences," Artificial Intelligence, vol. 267, pp. 1–38, 2019.

[120] C. DWORK, M. HARDT, and T. PITASSI, "Fairness through awareness," in Proceedings of the 3rd Innovations in Theoretical Computer Science Conference, 2012.

[121] M. CUMMINGS, "Artificial intelligence and the future of warfare," Chatham House, London, UK, 2017.

[122] B. SHNEIDERMAN, "Human-centered artificial intelligence: Reliable, safe & trustworthy," International Journal of Human–Computer Interaction, vol. 36, no. 6, pp. 495–504, 2020.

[123] J. W. CRANDALL, M. OUDAH, F. ISHOWO-OLOKO, S. ABDALLAH, J.-F. BONNEFON, M. AZIZ, and I. RAHWAN, "Cooperating with machines," Nature communications, vol. 9, no. 1, pp. 1–12, 2018.

[128] E. HORVITZ, "Principles of mixed-initiative user interfaces," in Proceedings of the SIGCHI conference on Human factors in computing systems, 1999, pp. 159–166.

[129] P. R. DAUGHERTY and H. J. WILSON, Human + Machine: Reimagining Work in the Age of AI. Harvard Business Review Press, 2018.

[130] A. F. COOPER and E. MOSS, "Accountability in an Algorithmic Society: Relationality, Responsibility, and Robustness in Machine Learning," ACM Conference on Fairness, Accountability, and Transparency (FAccT '22), 2022.

[131] I. B. WEINER and R. L. GOLD, Handbook of Psychology, Clinical Psychology, vol. 8. John Wiley & Sons, 2012.

[132] C. B. FREY and M. A. OSBORNE, "The future of employment: How susceptible are jobs to computerisation?," Technological Forecasting and Social Change, vol. 114, pp. 254–280, Jan. 2017.

[133] E. BRYNJOLFSSON and A. McAFEE, The second machine age: Work, progress, and prosperity in a time of brilliant technologies. WW Norton & Company, 2014.

[134] D. H. Autor, "Why are there still so many jobs? The history and future of workplace automation," Journal of Economic Perspectives, vol. 29, no. 3, pp. 3–30, 2015.

[135] T. H. DAVENPORT and J. KIRBY, Only humans need apply: Winners and losers in the age of smart machines. Harper Business, 2016.

[136] P. R. DAUGHERTY and H. J. WILSON, Human + Machine: Reimagining Work in the Age of AI. Harvard Business Review Press, 2018.

[137] J. BESSEN, Learning by doing: The real connection between innovation, wages, and wealth. Yale University Press, 2015.

[138] D. ACEMOGLU and P. RESTREPO, "Artificial intelligence, automation, and work," in The economics of artificial intelligence: An agenda. University of Chicago Press, 2018, pp. 197–236.

[139] F. ROSSI, "Building trust in artificial intelligence," Journal of International Affairs, vol. 72, no. 1, pp. 127-134, 2018.