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Masterarbeit

Industry Practices and Challenges of Using AI Planning: An Interview-Based Study

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Kurzfassung

In der sich rasch entwickelnden Landschaft industrieller Anwendungen haben sich KI-Planungssysteme als wichtige Werkzeuge zur Optimierung von Prozessen und Entscheidungsfindung herausgestellt. Die Implementierung und Integration dieser Systeme bringt jedoch erhebliche Herausforderungen mit sich, die ihre Wirksamkeit beeinträchtigen können. Diese Arbeit befasst sich mit der dringenden Notwendigkeit, die Best Practices und Herausforderungen zu verstehen, die mit der Entwicklung, Integration und Bereitstellung von KI-Planungssystemen in industriellen Umgebungen verbunden sind. Ohne dieses Verständnis riskieren Branchen eine ineffiziente Implementierung, die zu schlechter Leistung und Widerstand seitens der Endbenutzer führt.

Diese Forschung verwendet eine detaillierte Methodik, die eine Literaturrecherche und Interviews mit Branchenexperten und Forschern umfasst, um gängige Strategien und Hindernisse zu identifizieren, mit denen Praktiker konfrontiert sind. Die Studie beginnt mit der Untersuchung vorhandener Literatur, um berichtete Best Practices und Herausforderungen bei KI-Planungssystemen aufzudecken. Interviews bieten zusätzliche Perspektiven, bereichern die gesammelten Daten und gewährleisten eine gründliche Analyse.

Die Ergebnisse enthüllen eine Reihe von Best Practices, darunter die Bedeutung fachübergreifender Zusammenarbeit, robuster Datenverwaltungsstrategien und iterativer Entwicklungsprozesse. Darüber hinaus werden wiederkehrende Herausforderungen wie Integrationskomplexitäten, Skalierbarkeitsprobleme und die Notwendigkeit einer kontinuierlichen Systemevaluierung identifiziert. Diese Erkenntnisse heben kritische Bereiche mit Verbesserungsbedarf hervor und bieten praktische Empfehlungen zur Verbesserung der Effektivität von KI-Planungssystemen in industriellen Anwendungen.

Abstract

In the rapidly evolving landscape of industrial applications, AI planning systems have emerged as critical tools for optimizing processes and decision-making. However, implementing and integrating these systems present significant challenges that can hinder their effectiveness. This thesis addresses the urgent need to understand the best practices and challenges involved in designing, integrating, and deploying AI planning systems in industrial settings. Without this understanding, industries risk inefficient implementation, leading to poor performance and resistance from end-users.

This research employs a methodology that includes a literature review and interviews with industry professionals and researchers to identify common strategies and obstacles practitioners face. The study examines existing literature to uncover reported best practices and challenges in AI planning systems. Interviews provide additional perspectives, enriching the data collected and ensuring a thorough analysis.

The findings reveal best practices, including the importance of cross-disciplinary collaboration, robust data management strategies, and iterative development processes. Additionally, recurring challenges such as integration complexities, scalability issues, and the need for continuous system evaluation are identified. These insights highlight critical areas for improvement and offer practical recommendations for enhancing the effectiveness of AI planning systems in industrial applications.

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1 Introduction

The opening chapter of this thesis delves into the motivation for this research, emphasizing the significance of examining AI planning systems within industrial environments. It then presents the central research question that drives the study. Following this, it lays out the main objectives of the research, specifying the particular goals we intend to accomplish. Lastly, it offers a summary of the thesis structure, explaining the organization of the chapters.

1.1 Motivation

In today's rapidly evolving world, the integration of AI planning systems is paramount in maintaining the efficiency of industrial operations, all while reducing the requirement for human labour, allowing the industries to maintain a competitive advantage over one another. AI planning systems, which encompass techniques and algorithms for automated decision-making and process optimization, have become indispensable tools in industrial settings, an example of which is depicted in the next paragraph.

In manufacturing, AI planning can optimize production schedules by analyzing numerous variables such as machine availability, maintenance schedules, and supply chain logistics, resulting in reduced downtime and increased throughput [CPRK17]. Moreover, in healthcare, AI planning assists in organizing the medicinal routine of the patient, based on the pre-existing conditions that the patient might be suffering from [RMW+22]. Additionally, AI planning systems have expanded their domain of usage to automated driving, where automated driving, which is usually a real-life scenario, is converted into a planning problem and using the HTN planning model, generates suitable plans that can be used in real-life scenarios [AGPA22]. In cloud deployment, AI planning systems are used to reduce the complexities and errors that can be caused when using predefined scripts and in return, The industry can gain significant advantages from automated planning, including enhanced support for product variability and the ability to conduct sophisticated searches within large solution spaces [GNLA17]. Another use of an AI planning system is to reduce the time required for the migration of data from one cloud base to another, without having to wait for days to manually generate a plan [SVRL19]. AI planning systems are also implemented for automated Semantic Web service composition [HVB+13].

Despite their potential, the implementation of AI planning systems in industrial settings is fraught with challenges. One major challenge is executing a comprehensive software development lifecycle tailored to the application domain's needs [Geo23a] [Geo23b]. This process can be extremely complex, depending on the system requirements and the expertise of the engineers involved. Additionally, there is a lack of tools that support all aspects of AI planning system implementation. This necessitates the manual integration of several heterogeneous planning tools, each with different software, design, and configuration requirements. This manual process of combining, integrating, and deploying these systems is not only time-consuming and error-prone but also demands significant planning and technical expertise from practitioners [GB21]. Experts are crucial in constructing the domain model, which must align with the chosen planning language and tool. Their ongoing involvement is essential to ensure the model meets the specific requirements of the system [CFG+07] [Geo24]. This necessitates a comprehensive understanding of the internal workings of the planning software [GA15], which can be a daunting task for some due to constraints such as limited time or insufficient prerequisite knowledge. Another major obstacle in the pre-requisite knowledge of domain model for AI planning, and that it can be a laborious process transforming knowledge from other sources into a representation that is understandable by the planning system [Geo24].

Limited research has explored the current industry practices of AI planning. Except for [Hed23], which involves identifying and analyzing the common engineering challenges faced when engineering planning-based systems in industrial settings using exploratory methods, no other research efforts are known to us. Consequently, there is a lack of understanding regarding the processes and techniques that companies employ for AI planning. Analyzing industry practices in this area could reveal common challenges, highlight successful practices and processes, and identify gaps and shortcomings. Therefore, we undertake an analysis of the industry's current state of AI planning practices.

1.2 Research Question

The main research question this work aims to address is the following:

Which design, integration, and deployment best practices and challenges are common when engineering AI planning systems in industrial settings (i.e., industry and industrial research)?

This question is fundamental to understanding how AI planning systems can be effectively utilized to enhance industrial operations and to determine whether new approaches, methods, and tools are needed to enable the use of AI planning. It seeks to uncover the strategies that practitioners employ to successfully design, integrate, and deploy these systems, as well as the obstacles they frequently encounter. The focus is on identifying patterns and commonalities across different industrial applications to derive actionable insights.

1.3 Objective

The primary objectives of this research are to identify and document best practices in the design, integration, and deployment of AI planning systems in industrial settings. This involves understanding the methodologies and strategies that lead to successful implementations. Additionally, the research aims to investigate and analyze the recurring challenges faced by practitioners, such as issues related to integration, scalability, data management, and continuous system evaluation. By gathering firsthand insights from industry professionals, developers, and researchers through interviews [WHH06], the study seeks to capture a diverse range of perspectives and experiences.

The research also aims to provide actionable recommendations based on the findings derived using the method of meta-summary generation [RCSF14], addressing both best practices and challenges to offer practical guidance for industry professionals. Furthermore, this study intends to contribute to the existing body of knowledge in both academic and industrial domains, enhancing the understanding of AI planning systems and their application in industrial settings.

1.4 Structure

This thesis is structured to explore AI planning systems in industrial settings. The second chapter offers background information, defining AI planning systems and their applications in industrial contexts, and describing the relevant industrial settings.

The third chapter discusses existing literature on AI planning systems, focusing on best practices and challenges when using AI planning in industries. The fourth chapter details the design of the study, including the research methodology, the method used to collect data, the purpose and structure of the interview with the professional background of the interviewees.

The fifth chapter describes the implementation details and summarizes the insights gained from the interviews. The sixth chapter focuses on validating and evaluating the study, discussing the data analysis process, identifying common best practices, and highlighting recurring challenges practitioners face.

Finally, the seventh chapter addresses the conclusions and outlook. This chapter synthesizes the research findings, answering the central research questions comprehensively. It critically analyzes the study's limitations, discussing constraints such as data availability, methodological challenges, and the scope of the research. Furthermore, it outlines ideas for future work, suggesting how subsequent research can build upon the findings presented in this thesis to further advance the field of AI planning systems in industrial applications.

2 Background

To establish a comprehensive foundation for this research, it is essential to understand the core concepts and contexts in which AI planning systems operate. This chapter provides an in-depth overview of AI planning systems, defining their fundamental principles and exploring their diverse applications within industrial settings. Additionally, it describes the industrial contexts relevant to this research, highlighting the specific environments and scenarios where AI planning systems are implemented. By elucidating these key areas, this chapter sets the stage for a detailed examination of the design, integration, and deployment challenges and best practices associated with AI planning systems in industry.

2.1 Industrial AI

Before delving into the specifics of AI planning systems, it is crucial to discuss the broader rise of artificial intelligence in an industrial context. Understanding this evolution provides essential context for the development and application of AI planning systems, highlighting the transformative impact AI has had on industrial operations. This chapter will therefore begin by examining the emergence and integration of AI technologies in industry, setting the stage for a detailed exploration of AI planning systems and their significance within these environments.

Industrial AI, in broader terms, can be described as a systematic discipline focusing on the development, validation, and deployment of AI solutions at an industrial level. Therefore, we can say that industrial AI is a research in which domains such as Machine learning, Natural language Processing, and robotics work together, to achieve a common goal depending on the industrial sector they are deployed in [PJL+20]. The combination of these fields imbues the system with the ability to adapt and solve problems within pre-defined system boundaries through a certain degree of autonomous system.

To differentiate Industrial AI from traditional AI, there are five particular dimensions [PJL+20]:

1. Infrastructure: There is a strong emphasis on both the hardware and software utilized to ensure the highest level of capability, reliability, security, and interconnectivity. These factors are critical to achieving optimal performance and safeguarding industrial operations.

2. Data: The data used in industrial AI is characterized by the large volume, high-velocity variety and comes from various data sources.

3. Algorithms: The algorithms require a combination of physical, digital, and heuristic knowledge.

4. Decision-making: Since the system is used in industrial settings, the tolerance for errors is very low, with exception handling having the utmost priority. Efficiency is of special importance for large-scale optimization.
5. Objectives: Industrial AI addresses mostly concrete value creation through a combination of factors such as scrap reduction, improved quality, augmented operator performance, or accelerated ramp-up times.

2.2 Classification of Industrial AI

Including the classification of Industrial AI in this thesis, despite its current limited practical application, serves several important purposes. This classification traces AI's development from specialized applications to possibly more homogeneous systems, helping to choose the right technologies and methods. By understanding various AI levels, researchers and practitioners can delve into innovative solutions, encourage long-term strategic planning, and spark academic discussions, ultimately leading to more effective and forward-thinking industrial AI planning systems.

Industrial AI can be classified according to generality, technologies, and maturity[ZML19].

2.2.1 According to Generality

1. Specialized Industrial AI (Special I-AI): Applications of artificial intelligence, such as computer vision and speech recognition, are implemented in specific functions and targeted areas within industries.
2. General Industrial AI (General I-AI): The industrial system possesses the capability to perform all tasks within the industrial process, similar to human abilities. The crucial aspect is that the machine can autonomously identify tasks and adapt.
3. Super Industrial AI (Super I-AI): The industrial system attains self-awareness, including its own set of values, worldviews, and independent thought processes [ZML19].

2.2.2 According to Technology

1. Computational Intelligence: This form of AI is characterized by its rapid computation capabilities and memory storage. In industrial processes, machines perform at or beyond human levels in terms of computing and information transmission. It primarily encompasses elements like artificial neural networks and algorithmic programming.
2. Perceptual Intelligence: Industrial systems utilizing this type of AI depend on technologies for data acquisition and sensing. It mainly involves applications such as speech recognition and machine vision.
3. Cognitive Intelligence: This level of AI endows industrial systems with intelligent functionalities, including self-adaptation, autonomous decision-making, self-organization, and self-learning capabilities [ZML19].

2.2.3 According to the Maturity

1. Industrial Artificial Narrow Intelligence (I-ANI): This level of AI endows industrial systems with basic intelligent functions to accomplish specific industrial tasks, such as speech recognition, image recognition, and translation. It excels in particular aspects of artificial intelligence, focusing on specialized functions.
2. Industrial Artificial General Intelligence (I-AGI): At this level, the industrial system can perform reasoning, knowledge acquisition, planning, learning, communication, perception, movement, and manipulation of objects. It can think and make decisions independently, much like a human.
3. Industrial Artificial Superintelligence (I-ASI): Defined by Oxford philosophers and renowned AI thinkers, including Nick Bostrom, as an intelligence that surpasses the smartest human brains in nearly all domains, including scientific innovation, general knowledge, and interaction skill [ZML19].

2.3 AI planning systems

Planning is defined as the process of creating a sequence of actions designed to achieve a specific goal within a complex domain. In the planning domain, the effectiveness and outcomes of each action depend significantly on the current state of the world in which they are performed [Wil90].

To achieve goal-oriented behaviour, Artificial Intelligence Planning systems select available actions to alter the state of the environment, thereby satisfying the user's goal. The state model is well-suited for this purpose. It is a standard model in AI, defined over a state space consisting of a set of states and a set of actions that deterministically transition each state to another. When systems using the state model have complete knowledge about the states, the model is considered fully observable. Most planning approaches in AI rely on the concept of the state model [AG19].

A state model M comprises five components:

1. S: a finite set of states,
2. $s_0 \in S$: the initial state,
3. $S_G \subseteq S$: the set of goal states.
4. A: a finite set of actions,
5. δ : S × A → S δ:S×A→S: a deterministic transition function [AG19].

An initial state and a goal state description define a problem in AI planning. The initial state description provides the planning system with information about the current state of the world. The goal state description outlines the desired state of the world once the plan has been executed. The environment where planning occurs is often referred to as the application domain. The goal state description is sometimes simply called the goal. In many systems, a goal can be broken down into a set of smaller, simpler goals known as subgoals [HTD90].

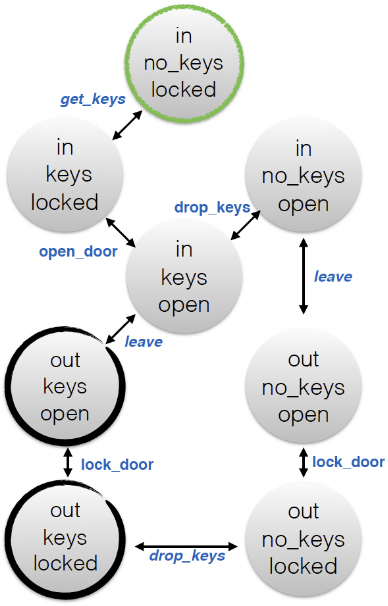

Figure 2.1: Example of a State Model [AG19]

The input to a typical AI planning system includes a set of operator schemata and a problem characterized by an initial state description and a specified goal. The initial state description details the current conditions, while the goal outlines the desired outcome. The output produced by the planner is a detailed plan that, when executed, is projected to achieve the defined goal. Several terms refer to the process that transforms the input into the output. It is commonly known as plan generation, synthesis, or construction. This process involves systematically creating and assembling a sequence of actions designed to transition the system from the initial state to the goal state, ensuring that all constraints and requirements are met along the way.

Scheduling entails establishing resource and temporal constraints that are applied to activities aimed at achieving a specific goal [VK20]. Scheduling is relevant because it ensures that resources and time are efficiently allocated to activities, enabling the achievement of specific goals by meeting temporal and resource constraints. There are three key aspects to consider in scheduling:

1. The essence of scheduling problems lies in reasoning about time and resource allocation.
2. Scheduling problems typically involve optimization, focusing not just on finding any solution but on identifying the optimal solution.
3. Scheduling problems require making decisions, often involving multiple alternative resources with varying costs and durations.

In particular, a planning system must monitor and reason about various world states at different moments in time. This requirement distinguishes planning from similar tasks such as scheduling and makes it inherently challenging, as it involves solving multiple exponential problems. Confronted with this immense complexity, planning becomes a significantly difficult endeavour. [Wil88]

AI planning systems use different types of planning approaches, some of which are defined in Subsection 2.3.1.

2.3.1 Types of Planning Techniques

This subsection provides an overview of the various planning techniques employed in AI planning systems to highlight their diverse approaches and applications and to inform the selection of the most appropriate algorithm for specific planning challenges. To keep the discussion concise, only the most commonly used planning algorithms are covered in this section.

1. Classical Planning [SFJ00]: In classical planning, the primary aim is to accomplish a defined set of goals. The goals and the initial state of the world are depicted using positive and negative literals. These literals are generally articulated through a language called the Planning Domain Definition Language (PDDL).
2. Temporal Planning [GNT16]: Temporal planning extends the classical model by incorporating durative actions, as opposed to instantaneous precondition-effect transitions. This enhanced model considers both a start point and a duration for each action. It requires that preconditions are met at the beginning of the action and that effects occur at the end.
3. HTN Planning [GA15]: Hierarchical Task Network (HTN) planning is an AI planning technique that deviates from traditional classical planning. This technique begins with an initial state description and a task network as the goal, alongside domain knowledge comprising networks of both primitive and compound tasks. A task network illustrates a hierarchy of tasks, where each task can either be executed directly if it is primitive or further decomposed into more detailed subtasks if it is compound. The planning process initiates by decomposing the initial task network and continues until all compound tasks have been broken down into primitive tasks, resulting in a solution. This solution is a plan that consists of a sequence of primitive tasks that can be applied to the initial world state.

2.4 Industrial Applications

2.4.1 Introduction

AI planning systems have found applications across a broad spectrum of industrial contexts, each presenting unique challenges and opportunities. These contexts range from manufacturing and logistics to energy and healthcare, where the ability to plan and execute complex sequences of actions efficiently is paramount. This section explores the industrial contexts where AI planning is particularly relevant, highlighting the specific needs and benefits in each area.

2.4.2 Manufacturing

In the manufacturing industry, AI planning systems are crucial for optimizing production schedules, managing inventory, and improving overall operational efficiency. The complexity of modern manufacturing processes, which often involve numerous interconnected steps and dependencies, necessitates advanced planning capabilities. AI planning can automate and optimize these processes, reducing downtime, minimizing waste, and ensuring that production targets are met. For instance, AI-driven predictive maintenance can schedule machine repairs proactively, avoiding unexpected breakdowns and costly delays [CPRK17].

2.4.3 Business Process Management

AI planning has significant applications in Business Process Management (BPM), particularly in optimizing and automating the creation and maintenance of business processes. For instance, at SAP, AI planning is used to automatically compose process skeletons by utilizing existing semi-formal models of software behaviour. This approach enables the rapid generation of business processes that align closely with IT infrastructure, thereby reducing the effort and costs associated with manual process implementation. The integration of AI planning in BPM facilitates more agile and responsive business operations, providing a robust framework for handling the dynamic and complex nature of modern industrial environments [HWK09].

2.4.4 Energy Sector

In the energy sector, AI planning systems are used to optimize the generation, distribution, and consumption of energy. Effective planning is critical to balance supply and demand with the increasing complexity of energy grids and the integration of renewable energy sources. AI planning can forecast energy usage patterns, schedule maintenance for energy infrastructure, and optimize the operation of power plants. This ensures a reliable energy supply, reduces operational costs, and enhances the overall efficiency of energy systems [GSA23] [GNN+17].

2.4.5 Healthcare

Healthcare is another industry where AI planning systems have a significant impact. Efficiently managing hospital operations, scheduling surgeries, and optimizing the allocation of medical resources are critical for providing high-quality care. AI planning can help schedule appointments, manage patient flow, and ensure that medical staff and equipment are used effectively. This leads to reduced waiting times, improved patient outcomes, and more efficient use of healthcare resources. In addition, AI planning is used to develop personalized treatment plans, taking into account each patient's specific needs and conditions [RMW+22].

2.4.6 Parking Space Management

AI planning addresses the complex challenge of parking space navigation in multi-storey car parks, which is essential in urban areas with increasing vehicle numbers. By modelling the task using the Planning Domain Definition Language (PDDL), AI planning generates optimal routes and parking strategies, considering multiple entry and exit points and the parking lot's state [XLRL22].

2.4.7 E-Commerce

In e-commerce logistics, AI planning plays a vital role in efficiently managing multiple mobile robots in automated warehouses to keep up with the increasing demand for same-day delivery. This involves solving Deadline-Aware Multi-Agent Tour Planning (DA-MATP) problems, where the goal is to maximize the number of orders packed on time. Advanced algorithms like ROSETTA, which utilize large neighbourhood search techniques, have shown significant improvements in order completion rates and overall warehouse throughput. This strategy boosts operational efficiency and helps e-commerce companies meet strict delivery commitments, leading to higher customer satisfaction and a competitive edge [HSC+23].

2.4.8 Aerospace

In the context of space missions, AI planning systems are essential for the scheduling, maintenance, and operation of spacecraft. AI can optimize mission timelines, manage crew activities, and ensure timely maintenance of onboard systems. This enhances mission safety, reduces the risk of delays, and improves overall mission efficiency. For instance, predictive maintenance powered by AI planning can anticipate potential issues with spacecraft systems and schedule necessary repairs before they lead to critical failures or jeopardize the mission [BJMR+05] [DFCM23].

3 Related work

This chapter explores the current research on the practices and challenges of implementing AI planning systems in industrial contexts. It provides an in-depth discussion of existing studies that highlight the challenges faced by practitioners, specifying the particular domains where these issues are most prevalent. By examining the difficulties encountered in various industrial applications, this chapter aims to offer a comprehensive understanding of the challenges in implementing AI planning in an industrial context and its impact.

'Towards Automated Planning for Enterprise Services: Opportunities and Challenges' dives [Vuk+19] into the use of AI for planning in enterprise IT and business services. It outlines several hurdles in implementing and deploying these systems, such as the complexity of modelling planning tasks, the need for reliable tools, and the difficulties of integrating with existing systems. One significant point is that non-experts often find it challenging to choose the right planning tools, which hinders widespread adoption. The paper also addresses performance and resource consumption issues, highlighting the necessity for efficient planning algorithms and sufficient computational resources. It introduces the idea of planning portfolios, where using multiple planners can boost overall performance. Scalability and adaptability are crucial, as AI planning systems need to handle changing conditions and increasing workloads dynamically. Data collection and management are identified as critical challenges, with an emphasis on ensuring data accuracy and seamless integration from various sources. The authors suggest creating domain-specific tools to simplify the development of planning models, thereby lowering entry barriers. They also stress the importance of user engagement and education to build trust in AI systems, recommending comprehensive training and user-friendly interfaces. A high-level framework for AI planning is presented, covering design and run-time planning, allowing for plan adjustments as needed. The paper highlights practical applications and benefits through use cases in IT service management, change management, event management, and robotic process automation (RPA). Another key practice discussed is the successful integration with existing systems, which involves developing APIs and middleware for smooth communication between new AI modules and legacy systems. Continuous improvement and learning are advocated, with regular updates and refinements based on user feedback and performance data.

'Towards Engineering AI Planning Functionalities as Services' [Geo23c] explores the challenges and practices in developing AI planning systems for industrial applications. It highlights the complexity of integrating planning components due to a lack of established mechanisms for system design, interoperability, and deployment. Key issues include the intricate nature of existing planning tools, difficulty in maintaining functional boundaries and ensuring interoperability. The authors propose using service-oriented computing principles and architectural patterns to address these challenges. This involves defining fine-grained planning functionalities and encapsulating them as interoperable and portable services. By adopting standard interfaces and minimal operations, the integration process is simplified, enhancing flexibility and reusability. Additionally, the paper advocates for containerization to package and deliver planning services, reducing the technical expertise required for deployment. Continuous monitoring and logging of planning systems' performance are emphasized, with the use of Message-Oriented Middleware (MOM) and the Hub-and-Spoke pattern for improved scalability and flexibility. The Strategy pattern is proposed to address the heterogeneity in planning techniques, allowing for the runtime selection of appropriate strategies. In summary, the paper provides insights into the challenges and practices of AI planning in industrial settings, focusing on implementation complexity, interoperability, reuse, integration, and continuous improvement. The proposed service-oriented approach and architectural patterns offer practical solutions for developing and deploying advanced AI planning systems in various industries.

'A Vision for Composing, Integrating, and Deploying AI Planning Functionalities' [GB21] delves into the challenges and strategies for engineering AI planning systems in industrial contexts. It highlights the difficulties of integrating heterogeneous planning tools, which are not originally designed for seamless composition and interoperability. The paper emphasizes the complexity of current planning tools, their diverse data models, and the substantial effort required for manual integration and deployment, making it a time-consuming and error-prone process. The authors propose a vision of using service-oriented computing principles to modularize planning functionalities into distinct, interoperable services. This approach aims to facilitate the composition, integration, and automatic deployment of AI planning systems. They suggest leveraging standardized interfaces and containerization to package planning services, ensuring they are portable and can be easily integrated into various environments. The paper underscores the importance of automated deployment and management to reduce the technical expertise required and enhance system scalability and adaptability. In terms of practical applications, the paper discusses the use of AI planning in domains such as building automation, where different components must work together to achieve objectives like energy efficiency and occupant comfort. It outlines a four-step process for designing and deploying integrated planning systems, including creating logical composition models, generating integration models, and transforming them into executable deployment models. Overall, the paper offers a comprehensive framework for addressing the engineering challenges in AI planning, focusing on the need for modularity, loose coupling, portability, and automated management. This approach aims to streamline the development and deployment of advanced AI planning systems, making them more efficient and adaptable to industrial needs.

'Integrated A.I. Systems' [Thó07] delves into the complexities and challenges associated with integrating various AI planning functionalities to create robust and efficient AI systems. Thórisson emphasizes a holistic approach to AI development, advocating for the integration of diverse cognitive mechanisms to replicate general-purpose intelligence, which is crucial for industrial applications. One of the major challenges identified is the lack of effective methods for system integration. The paper highlights the necessity of developing tools for building large architectures and design methodologies specifically tailored for real-time AI systems. This approach addresses the fundamental issues of interoperability and integration, which are critical for deploying AI planning systems in industrial contexts. Thórisson also underscores the importance of community-level code sharing and systematic knowledge accumulation to enhance the development and deployment of AI planning systems. By facilitating collaboration among researchers and practitioners, the paper suggests that the AI community can overcome existing barriers and accelerate progress in AI planning.

‘SOA-PE: A Service-Oriented Architecture for Planning and Execution in Cyber-Physical Systems’ [FMJB15] addresses the complex challenges of developing and deploying AI planning systems for large-scale cyber-physical systems (CPS). A primary challenge is implementing a decentralized, multi-agent architecture capable of managing CPS’s heterogeneous and distributed nature. The need for flexible and scalable architecture to handle diverse agent capabilities is critical, complicating coordination and communication. Interoperability and integration of planning tools are significant hurdles. The service-oriented architecture (SOA) modularizes functionalities into independent services to enhance reusability and simplify integration, requiring standard interfaces and minimal operational coupling. Reusing tightly coupled planning components poses difficulties, which the architecture aims to mitigate through modularity and interchangeable services. Development and deployment are challenging, particularly regarding scalability and adaptability. Containerization and automated deployment methods are emphasized to reduce technical expertise requirements. Ensuring dynamic adaptation and scalability of systems in changing environments is essential yet complex. Data management and monitoring are additional obstacles. Effective data collection, integration, and real-time monitoring are vital for continuous operation and improvement. The architecture supports data aggregation, analysis, and feedback mechanisms for dynamic re-planning and adaptation. Process-related challenges, including maintaining system flexibility, ensuring high performance, and supporting continuous improvement, are addressed through the proposed architecture. The service-oriented approach facilitates iterative development and deployment, allowing refinements based on user feedback and real-world performance data. Achieving a balance between flexibility, reliability, and efficiency in complex systems remains a significant challenge.

‘An Exploration of Challenges in Engineering AI Planning Systems’ [Hed23] focuses on exploring and addressing the challenges associated with engineering AI planning systems in industrial contexts. The study identifies and analyzes the key obstacles faced by professionals in the field through a combination of literature review, conceptual modelling, and an empirical survey of industry experts. The thesis begins with a detailed background on AI planning, highlighting its importance in various domains and the specific engineering challenges it presents. This foundational understanding sets the stage for a more focused exploration of these challenges in real-world applications. The conceptual model developed in this study is based on existing literature and is designed to provide a structured approach to understanding the complexities of AI planning systems. This model is then tested against the empirical data gathered from a survey targeting professionals actively engaged in AI planning. The survey results reveal several critical insights into the challenges faced by practitioners. These include issues related to documentation and support, the impact of complexity on performance, tool interoperability and integration, standardization and reusability, and the practical difficulties of deploying AI planning tools in real-world settings. Each of these areas is explored in depth, with the findings used to validate the conceptual model. The discussion section of the thesis synthesizes these findings, offering a comprehensive analysis of the current state of AI planning in industrial contexts. It highlights the need for improved documentation, better management of complexity, enhanced interoperability and integration practices, and more robust deployment strategies.

4 Design of the Study

This chapter will offer a comprehensive and detailed description of the methodology employed to achieve the research objectives and uncover the answers to our key questions. We will begin by outlining the overall methodology followed throughout the study. Subsequently, we will delve into formulating the questions and explaining the rationale behind their design. The steps followed for the data collection are discussed. Finally, we will detail the selection criteria for our participants and provide an overview of their professional backgrounds. This structured approach ensures a thorough understanding of the research process and the validity of our findings.

4.1 Methodology

The approach we have decided to adopt for this study is the Qualitative research method. Qualitative research focuses on studying subjects within their natural environment. A qualitative researcher aims to interpret a phenomenon based on the explanations provided by the participants. This research approach acknowledges that there are multiple ways of interpreting data and seeks to uncover the causes perceived by the subjects involved in the study. It is centred on understanding the participants' perspectives and their views of the problem at hand. The subjects are the individuals participating in the study to evaluate a specific object [WHH06] [RH09].

To achieve our goal, we are utilizing interviews to gather crucial data for our study. Given that our participants are professionals working in the AI planning industry, relying solely on quantitative methods would likely be insufficient. Numbers and values alone would not provide the depth of insight required to draw meaningful conclusions. Instead, qualitative data obtained through direct interactions will enable us to gain a comprehensive understanding of the challenges and best practices in the field.

4.2 Data Collection

For our research, a critical step was to gather extensive information on the challenges and applications of implementing AI planning systems across various industries. This in-depth understanding was essential to comprehensively analyze and address the intricacies involved in leveraging AI for industrial planning.

The data collection process was designed to gather comprehensive and in-depth insights into the usage of AI planning systems across various industries. This process involved conducting interviews with professionals.

This data collection was performed in the following steps:

1. Selection of Interviewees
   a) Identifying Key Sectors: We identified key sectors where AI planning systems are prominently used, including aerospace, automotive, gaming, robotics, healthcare, urban traffic control, and supply chain management.
   b) Targeting Experts: Within these sectors, we targeted professionals with substantial experience and expertise in AI planning systems. Criteria for selection included their roles in developing, implementing, and managing AI planning systems.
2. Structured Framework
   a) Preparation of Structured Framework: A structured interview framework was designed to ensure consistency and comprehensiveness across all interviews. This framework included both open-ended and specific questions aimed at uncovering detailed insights. The interview questions can be found in A and the description of each of the sections in the interview is referenced at 4.4.
   b) Determination of Key Areas of Focus: The interview questions covered areas such as professional background, specific applications of AI planning, development processes, performance measures, interdisciplinary collaboration, technical challenges, data collection methods, financial management, and learning strategies.
3. Conducting the Interview
   a) Contacting the Experts: Since our research targets a very specific group of professionals, it was crucial to identify individuals who met the criteria to effectively answer our questionnaire.
   b) Initial Phase of Outreach: In the initial phase, we utilized the website [AIP] to gather information about companies and professionals involved in industrial-scale AI planning. This platform provided valuable contacts who were directly engaged in relevant projects. Next, we reached out to researchers who had authored papers and articles on the implementation of AI planning at an industrial level. Additionally, we used LinkedIn to identify and contact other suitable participants. Through these efforts, we initially secured 7 participants. However, this number was insufficient to achieve a comprehensive understanding of our research objectives.
   c) Second Phase of Outreach: To enhance the robustness of our study, we entered a second phase of outreach. We contacted members of the [NAS] and continued to identify potential participants through additional research papers. Ultimately, these efforts allowed us to increase the number of participants to 10, ensuring a more thorough and reliable dataset for our thesis questionnaire.
   d) Transfer of Interview Question: Considering the global distribution of our interviewees and the varying time zones they were in, we determined that sending the interview questions via email would be the most practical and efficient approach. This method allowed us to accommodate their schedules, ensuring that each participant could provide thoughtful and comprehensive responses at their convenience. Additionally, email communication facilitated a smoother exchange of detailed information without the constraints of coordinating live interviews across multiple time zones.

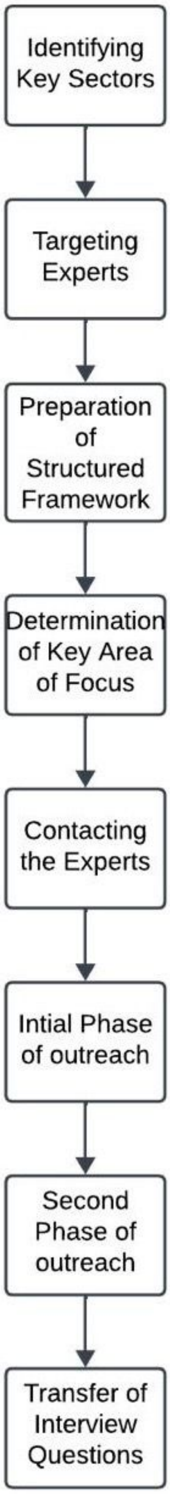

Figure 4.1: Steps Followed for Data Collection

4.3 Purpose of Interview

The purpose of our interviews is twofold: descriptive and exploratory [RH09]. Descriptively, we aim to thoroughly examine and document the current technologies being utilized within various industries. This includes understanding the specific tools, systems, and methodologies that are in place. Exploratory, we seek to gain deeper insights into the challenges that AI practitioners face in their daily work. This involves understanding the obstacles they encounter, the strategies they employ to overcome these challenges, and their overall experiences with AI planning systems. By combining these two approaches, we aim to develop a comprehensive understanding of both the current state of technology and the practical difficulties faced by professionals in the field.

4.4 Structure of the Interview

The interview for this thesis is meticulously structured to gather comprehensive and relevant data from AI planning practitioners. The interview is divided into several sections, each focusing on different aspects of AI planning systems in industrial settings. The main motivation for dividing the interview into sections stems from the need to focus on specific aspects of working with AI planning systems. This approach serves two primary purposes. Firstly, it ensures clarity for the interviewees, allowing them to understand the context of each set of questions and respond accurately without confusion. By providing clear labels for each section, interviewees can easily navigate through the questions. Secondly, this structured format facilitates ease of analysis, enabling a more organized and efficient interpretation of the data. By categorizing the questions, we can systematically analyze the responses and draw meaningful insights for each aspect of AI planning.

1. Professional Experience

   This section aims to understand the background and experience of the interviewees with AI planning systems. By discussing their current roles and the duration of their involvement with AI planning, we can gauge the depth of their expertise and their perspectives on the evolution of AI planning technologies in their industries.

2. Development Process

   This section explores the methodologies and principles followed in developing AI planning systems. Interviewees are asked to describe the guiding principles they adhere to when creating these systems for industrial use. Additionally, this section delves into the integration of AI planning systems into existing software architectures, highlighting specific tools and technologies essential for their development, such as the Fast Downward planner, Temporal planning, and Monte Carlo Tree Search.

3. Performance

   In this section, the focus is on assessing and maintaining the effectiveness and reliability of AI planning systems in real-world applications. Participants share their methods for evaluating system performance, implementing measures to ensure sustained performance and reliability during deployment, and practices that guarantee scalability and robustness under heavy usage.

4. Interdisciplinary Collaboration

   This section investigates the collaboration between different teams and the interdisciplinary nature of AI planning projects. It examines the size and composition of teams working on AI planning, the necessity of expertise in multiple domains (e.g., planning, software engineering, data science), and the facilitation of collaboration among team members from diverse backgrounds. Specific interactions between planning experts and software engineers are also explored to understand how interdisciplinary collaboration enhances project outcomes.

5. Technical Challenges

   This section focuses on the technical difficulties encountered and the solutions implemented in AI planning systems. Participants discuss common technical issues, describe significant challenges faced during system implementation, and share strategies for addressing unexpected results produced by AI planning systems. This section provides insights into the practical aspects of overcoming technical hurdles in AI planning.

6. Data Collection

   In this section, the process of data collection and analysis to support AI planning systems is examined. Interviewees explain how data is gathered, processed, and utilized to enhance the functionality and accuracy of AI planning systems, providing a deeper understanding of the data-driven nature of these systems.

7. Financial Management

   This section addresses the financial aspects of AI planning system projects. It compares the costs of AI planning projects with other types of projects and discusses strategies for managing these costs effectively. By understanding the financial implications, this section highlights the economic considerations essential for successful AI planning implementations.

8. Expertise in AI Planning

   This section looks at the level of expertise required for working with AI planning systems and how it is acquired. Participants describe the specialized knowledge needed for their roles, how they gained this expertise, and the aspects of AI planning where expert consultation is most frequently sought. Additionally, the sources for finding AI planning experts for collaboration or consultation are discussed.

9. Learning about AI Planning

   This section examines how practitioners keep their knowledge and systems up to date with technological advancements. Interviewees share their methods for ensuring that AI planning systems stay current, how they stay informed about the latest developments beyond academic research, and the opportunities available for system developers and practitioners to learn about AI planning. This section emphasizes the continuous learning and adaptation necessary in the rapidly evolving field of AI planning.

Each section of the interview is designed to extract specific insights related to the research objectives. By covering a broad range of topics from professional experience to technical challenges and interdisciplinary collaboration, the interview structure ensures that a holistic view of the current practices and challenges in AI planning systems is obtained. This structured approach will facilitate the collection of rich qualitative data, providing a solid foundation for the analysis and conclusions of this study.

The complete set of interview questions can be found in Appendix A.

4.5 Interviewees

To effectively reach the target audience, we utilized a combination of professional networking platforms, such as LinkedIn, and direct email communication. These mediums were chosen for their wide reach and ability to connect with professionals in the AI planning industry. Once potential interviewees were identified and contacted, they were provided with a comprehensive list of questions designed to gather in-depth insights. Additionally, an interview preamble was included, detailing the objectives and aims of our study. This preamble ensured that the participants fully understood the purpose of the research and the significance of their contributions. The preamble of the study can be found at B.

Different experts from various parts of the world, specializing in AI planning across different sectors, were contacted and interviewed. Fortunately, we obtained valuable responses from professionals with diverse backgrounds, which are summarized below:

1. One of the professionals interviewed is a NASA program area manager for the Advanced Multi-Mission Operations System (AMMOS) program. This program focuses on developing software that aids ground operators in navigating and operating spacecraft, primarily supporting deep-space planetary missions. With a decade of experience in spacecraft planning systems, he has a profound understanding of mission planning and scheduling intricacies. Over the past two years, he has specifically focused on AI planning systems, marking a significant shift from traditional procedural approaches. Historically, most spacecraft planning systems relied on straightforward procedures to layer activities in the mission plan sequentially, preventing conflicts and constraint violations. His expertise offers invaluable insights into the evolution of planning systems from procedural methods to AI-enhanced frameworks, highlighting the trans-formative potential of AI in managing complex space missions.

2. Another interviewee is the AI Systems Integration Manager at an automotive company. With two years of experience working with AI planning systems, his focus has been on optimizing production lines and logistics through AI-driven solutions. In his role, he has leveraged AI technology to streamline and enhance the efficiency of manufacturing and assembly processes, improving overall productivity.

3. One of the respondents is a Demand Planning Projects Specialist with 2.5 years of experience in AI planning systems. He has concentrated on leveraging AI to enhance demand forecasting, inventory management, and supply chain optimization, contributing to more efficient and effective operations

4. Another expert interviewed is a Professor of AI at the University of Huddersfield, with extensive experience in AI planning since 2009. In 2014, he began focusing on real-world applications of AI planning, particularly in traffic control. Collaborating with Simplifai

Systems Ltd, a company in which he is a shareholder, he has developed and implemented AI-driven solutions to improve traffic flow, reduce congestion, and enhance public safety. His dual role as an academic and industry collaborator provides a unique perspective on the practical and theoretical aspects of AI planning systems.

5. Another professional we spoke to is an AI Software Developer who has been in this role for the past year. He works on various projects related to the development and implementation of AI planning systems across different industrial sectors, contributing to advancements in AI technology and its applications.

6. A Senior Principal Programmer at Guerrilla, a renowned games company, also shared his insights. His introduction to planning systems began in 2005 when Guerrilla started using Hierarchical Task Networks (HTNs) to program the behaviour of non-player characters (NPCs) in Killzone 2 for the PlayStation 3 console. Before adopting HTNs, his team used a subsumption architecture for action selection and briefly experimented with an STRIPS-based planner. Ultimately, they chose HTNs for their ability to provide more direct control, essential for implementing the behavioural exceptions and idiosyncrasies demanded by game designers. His extensive experience in developing sophisticated AI planning systems for games offers valuable insights into the practical application and advantages of these technologies in the gaming industry.

7. The Operations Technology Manager at another company, with over three years of experience working with AI planning systems, also provided valuable input. His primary focus has been on enhancing supply chain operations and manufacturing efficiency through AI-driven solutions, optimizing various aspects of the supply chain.

8. We also interviewed a Lead Robotics Engineer with about four years of experience in AI planning systems. His primary focus has been on automating complex manufacturing processes and enhancing the intelligence of robotic systems, contributing to significant advancements in robotic automation and efficiency.

9. A Professor Emeritus at the University of Ottawa, who served as a Full Professor for over 20 years, shared his extensive experience. Throughout his distinguished academic career, he explored various AI paradigms in his research. Approximately seven years ago, he and his research team began utilizing automated planning in their MitPlan project, marking a significant development in their approach and leading to more efficient and effective planning processes.

10. Finally, a Software Architect in the Mission Planning, Sequencing, and Analysis group provided insights from his two years in the role. He focuses on developing and optimizing software solutions for mission planning and sequencing, ensuring that complex space missions are coordinated effectively and enhancing overall operational efficiency. His expertise highlights the critical role of AI in space mission planning and execution.

5 Realisation of the study

This chapter provides details on the implementation, explaining the methodologies used to process and analyze the collected data to ensure its reliability and relevance in concluding. The chapter concludes with a summary of the key insights gained from the interviews, offering a rich understanding of the practical experiences and perspectives of AI planning practitioners. This structured approach ensures that the study's findings are grounded in robust and comprehensive data, providing valuable contributions to the field of AI planning systems.

5.1 Implementation Details

We applied the Qualitative Metasummary technique to derive detailed insights from our interview data, as outlined by [RCSF14]. This method enabled us to systematically extract, group, abstract, and quantify the findings from our interviews, providing a robust synthesis of the empirical evidence gathered from professionals in AI planning systems across various industries. We followed the steps mentioned below:

1. Extracting Findings
   a) Definition of Findings: We started by defining a 'finding' from the interview data. This included significant statements or claims made by the interviewees related to the challenges and applications of AI planning systems.
   b) Identification and Extraction: Each interview transcript was thoroughly reviewed to extract relevant findings, which were identified as key insights, observations, and experiences shared by the professionals.
2. Grouping Findings
   a) Assembling Similar Topics: The extracted findings were grouped based on their thematic similarities, aligning with the questionnaire sections. This process involved organizing the findings into categories such as professional experience, development processes, performance assessment, interdisciplinary collaboration, technical challenges, data collection, financial management, AI planning expertise, and AI planning.
   b) Preserving Meaning: Care was taken to preserve the original meaning and context of the findings while grouping them to maintain the validity of the data.
3. Abstracting Findings
   a) Labeling and Organizing: After grouping, the findings were abstracted and labeled in a way that made them accessible and easy to understand. This involved creating comprehensive statements that encapsulated the essence of each group of findings.

b) Developing Abstract Statements: We moved back and forth between the findings, refining the abstract statements to ensure they accurately represented the grouped data while preserving the original context.

5.2 Interview Insight

After collecting the interview responses, it was crucial to identify the common themes across different industrial sectors for a clearer understanding. This section summarizes the insights gathered from professionals working in various fields, based on their interview answers. The complete interviews can be provided upon request.

5.2.1 Aerospace Sector

1. Development Process: The development of AI planning systems in the aerospace sector, particularly within NASA's Multi-Mission Ground Software Systems program, follows specific guiding principles and integration methods. The customer base, mainly deep space missions, necessitates a focus on user adoption and engagement. Transparency is a priority, with software being made open source to effectively serve the public. AI planning systems like the Fast Downward planner are integrated using a service-based architecture, exemplified by systems such as Aerie. This design supports various planning and scheduling algorithms, allowing customers to customize services or incorporate advanced AI techniques as needed. The integration process includes assessing compatibility, developing APIs for seamless communication with existing databases and software modules, creating detailed documentation, and conducting pilot tests to validate functionality before full-scale deployment. Custom middleware is developed when necessary to facilitate data flow and command execution between disparate systems.
2. Performance: The effectiveness of AI planning systems in the aerospace sector is measured through a combination of key performance indicators (KPIs), extensive simulations, and real-world trials. Metrics such as energy utilization and the number of planned activities are used to demonstrate the tangible benefits of AI planning systems. For example, NASA's Perseverance Rover project captures how much energy was "left on the tableüsing different planners and how many additional activities were planned with the onboard planner. Ensuring performance and reliability involves rigorous pre-deployment testing, continuous monitoring through logging and telemetry, and constant adjustment to address any deviations.
3. Interdisciplinary Collaboration: In aerospace, teams typically consist of 5-10 members with expertise in scheduling, planning, and software engineering. Collaboration is facilitated through scheduling workshops, educational seminars, and cross-disciplinary reviews to identify major issues and brainstorm potential solutions. This comprehensive approach promotes knowledge exchange and ensures high-quality outcomes, addressing collaboration challenges such as technical difficulties and workload distribution.
4. Technical Challenges: Significant challenges in implementing AI planning systems include gaining user trust, particularly within the science operations community, and managing the performance of planning and scheduling algorithms that require extensive computational

resources and time. Efforts to optimize performance include allowing users to provide hints about activity duration and conducting deep analysis to achieve scheduling explainability. However, these approaches often face limitations, necessitating ongoing refinement and rigorous testing.

5. Data Collection: Data collection is integral to the effectiveness of AI planning systems, involving real-time operational data, user feedback, and system logs. Machine learning algorithms and traditional data processing methods analyze the collected data, uncovering patterns and trends to refine planning algorithms and enhance predictive capabilities.
6. Financial Management: Financial management involves a technology infusion process, initially allocating a small budget to evaluate the potential integration of new ideas into existing product lines. If successful, the project is fully budgeted and implemented. Agile project management techniques and regular cost-benefit analyses ensure financial discipline and effective resource allocation.
7. Expertise and Learning: Professionals in the aerospace sector stay updated by attending conferences, reading literature, and collaborating with experts. Continuous learning and expert consultation are crucial for addressing complex planning issues and ensuring robust AI planning systems. Engagement with academic partnerships and industry conferences provides access to cutting-edge expertise and facilitates valuable knowledge exchange.
8. Learning about AI Planning: Professionals in the aerospace sector advance in AI planning through proactive communication with program management to secure necessary budgets for staying updated with the latest advancements. Financial support for ongoing education and training is crucial for continuous progress in this field. Access to industry conferences and academic papers helps experts stay informed about new inventions and developments. For new developers, learning opportunities include professional development courses, certification programs, and hands-on workshops provided by industry leaders and academic institutions

5.2.2 Gaming Sector

1. Development Process: The development of AI planning systems for action games follows principles focused on performance, adaptiveness, and rapid iteration. Performance is crucial due to the real-time nature of action games, where multi-agent systems must create and execute plans dynamically. AI planning systems must operate efficiently within the hardware's constraints, ensuring consistent performance across various configurations. Adaptiveness allows for flexible modifications to meet game designers' creative demands, prioritizing entertaining behaviours over purely optimal ones. Rapid iteration, essential for game development, involves extensive experimentation to refine the game's mechanics and AI behaviours. The HTN planner, inspired by the SHOP2 planner but custom-built, ensures tight integration with the game's architecture.
2. Performance: The effectiveness of AI planning systems in games is assessed both subjectively and objectively. Subjectively, it is gauged by the player experience, while objectively, it is measured through CPU profiling tools and telemetry to monitor and optimize performance.

Ensuring performance and reliability involves rigorous testing and validation processes to deliver a robust experience from the initial release, minimizing the need for post-deployment adjustments.

3. Interdisciplinary Collaboration: Collaboration between game designers and engineers is crucial for seamless integration of design and technical implementation. Teams typically involve up to 10 members, including art, rigging, modelling, effects, animation, audio, game code, and AI leads. Regular interactions ensure AI behaviour aligns with the overall game design vision. High-level NPC designs undergo thorough vetting by leads from all involved teams, maintaining efficiency and creativity in the game development process.

4. Technical Challenges: Technical issues such as unintended backtracking over multiple plan instantiations waste CPU time and impact performance. Custom tools and domain adjustments address these issues, optimizing the planning process and enhancing system efficiency. When AI systems produce unexpected results, deep analysis and debugging are conducted to identify the root cause and refine the system's logic and data flow.

5. Data Collection: Data collection involves gathering telemetry of various subsystems during development, visualized on a world map in the developers' editor. This helps identify performance hotspots and optimize the AI planning systems.

6. Financial Management: Financial management in game development involves retaining skilled engineers and managing costs through efficient resource allocation. Finding engineers familiar with specific AI planning technologies can be challenging, underscoring the importance of strong retention strategies to maintain a knowledgeable and experienced team.

7. Expertise and Learning: Expertise in AI planning is gained through conferences, research, practical experience, and collaboration with industry experts. Continuous learning is essential for staying updated with advancements in AI planning, and ensuring the application of cutting-edge techniques and tools.

8. Learning about AI Planning: In the gaming sector, staying current with technological advancements involves maintaining a development roadmap looking ahead by about five years. This helps in anticipating future needs and integrating relevant innovations. The team informally monitors innovations by other game developers and advancements in academia. Learning opportunities include recorded presentations on using planning in-game AI and articles from in-game AI programming books. However, AI planning is not a widely popular choice in game development, and learning opportunities are relatively limited, underscoring the need for more educational resources and integration into game design practices

5.2.3 Robotics Sector

1. Development Process: Developing AI planning systems for robotics emphasizes precision, efficiency, adaptability, and safety. Integration begins with analyzing existing software to identify integration points and developing custom APIs for seamless communication. Extensive testing and iterative feedback loops ensure functionality and safety. Temporal planning is crucial for tasks requiring precise timing, while techniques like Monte Carlo

Tree Search (MCTS) evaluate multiple action sequences to optimize outcomes. Simulation software models, tests, and refines robotic behaviors before deployment, reducing development time and enhancing safety.

2. Performance: Effectiveness is measured through metrics like task completion time, precision, error rates , and adaptability. Continuous monitoring, regular updates, and predictive maintenance ensure performance and reliability. Scalability is achieved through modular design, allowing easy updates and integration of new functionalities. Stress testing under simulated real-world conditions helps maintain robust and efficient AI planning systems capable of handling heavy use.
3. Interdisciplinary Collaboration: Teams of around 15 members include software developers, machine learning experts, and systems integrators. Collaboration is facilitated through interdisciplinary project teams and regular knowledge-sharing sessions. Agile methodologies manage projects, enabling frequent adjustments based on team input. This approach ensures cohesive teamwork and integrates diverse expertise effectively.
4. Technical Challenges: Challenges include integrating AI decision-making with real-time robotic movements and managing human-robot interaction unpredictability. Advanced sensors and optimized algorithms enhance safety and efficiency. When AI planning systems produce unexpected results, thorough analysis identifies discrepancies, leading to refinements in AI models or training data.
5. Data Collection: Data collection involves using sensors and cameras to capture real-time operational data. AI techniques analyze this data to refine task performance and identify optimization patterns. Continuous feedback loops ensure that AI planning systems are constantly improving and adapting to new conditions.
6. Financial Management: AI planning system projects in robotics often have higher costs due to their complexity and use of cutting-edge technology. Effective cost management includes developing projects in incremental stages, seeking partnerships with research institutions, and obtaining R&D funding. This approach ensures efficient resource use and reduces the risk of costly errors.
7. Expertise and Learning: Specialized knowledge in AI and robotics is essential, acquired through academic qualifications, hands-on experience, and ongoing professional development. Expert consultation enhances AI's ability to make autonomous decisions and integrate systems with existing robotic hardware. Collaboration with industry conferences, academic partnerships, and professional networks provides access to leading experts and innovative ideas.
8. Learning about AI Planning: To stay current with advancements in AI planning and robotics, professionals actively participate in technical symposiums, collaborate with universities and research institutions, and keep up with new publications in these fields. Following industry blogs, subscribing to relevant tech news outlets, and participating in online forums are also essential practices. Numerous learning opportunities are available, including specialized training programs, certification courses in AI and robotics, and practical workshops offered by technology providers and industry association

5.2.4 Urban Traffic Control

1. Development Process: Developing AI planning systems for urban traffic control involves understanding current and future challenges, ensuring engineered models support necessary reasoning, and maintaining transparency. Integration begins with prototyping using existing tools, followed by developing ad-hoc tools for production to ensure seamless integration with existing software. Temporal planning techniques and domain-specific heuristics optimize planning and decision-making processes.

2. Performance: Effectiveness is assessed through simulations and real-world trials, comparing system performance with historical data and user feedback. Extensive testing and analyzing problem specifications ensure the system can manage the expected workload and perform reliably under real-world conditions.

3. Interdisciplinary Collaboration: Teams typically consist of around 10 members with diverse backgrounds, including software developers, engineers, and AI experts. Collaboration involves regular meetings and joint problem-solving sessions, ensuring effective integration of design and technical implementation. Planning experts develop and document prototypes, implemented by software engineers.

4. Technical Challenges : Challenges include generating solutions within time bounds and integrating real-time sensor data. Improvements to knowledge models, ad hoc heuristics, and optimization of planning engines address these challenges. Unexpected results prompt thorough analysis and adjustments to system parameters and planning algorithms.

5. Data Collection: Data collection relies on historical data and real-time operational data stored in databases. Comprehensive data collection ensures robust and reliable AI planning systems capable of meeting real-world demands.

6. Financial Management: Financial management in urban traffic control is similar to other sectors, focusing on cost control and efficiency. Strategies include leveraging existing resources, adopting modular development approaches, and conducting thorough cost-benefit analyses.

7. Expertise and Learning: Expertise is acquired through academic degrees, work experience, and continuous learning. Expert consultation addresses specific knowledge encoding and optimization issues. Collaborations via conferences and professional networks provide valuable insights and enhance system effectiveness.

8. Learning about AI Planning: In the urban traffic control sector, professionals keep up with major trends by attending conferences and reading research papers. Other resources include planning wikis and planning domains to gain knowledge in the field. This approach ensures that AI planning systems remain updated with technological advancements

5.2.5 Healthcare Sector

1. Development Process: AI-based systems in healthcare utilize both vanilla and temporal planning to address straightforward and complex, time-sensitive operations. Vanilla planning focuses on sequences of actions without considering time, suitable for simple tasks, while

temporal planning incorporates the dimension of time, handling action durations and scheduling for more complex operations. This dual approach ensures comprehensive solutions for healthcare AI systems.

2. Performance: Performance is assessed through realistic case studies, providing benchmarks to evaluate the system's effectiveness in fulfilling tasks and objectives. Deployment focuses on maintaining patient safety, ensuring alignment with existing workflows, and integrating AI planning systems to enhance efficiency and support patient care.
3. Interdisciplinary Collaboration: Teams of 5-8 members include planning experts, software engineers, and medical collaborators. Collaboration involves structured briefings to ensure all team members understand the clinical problems addressed. Medical collaborators focus on their expertise while technical team members integrate their knowledge effectively, fostering a productive development environment.
4. Technical Challenges: Challenges include mitigating conflicting clinical practice guidelines and manually incorporating dynamic external knowledge into planning models. Continuous refinement and error checking address these challenges, ensuring robust and reliable AI planning systems in healthcare.
5. Data Collection: Data collection involves clinical practice guidelines and electronic health records, requiring careful management to ensure privacy and regulatory compliance. Secure and efficient data handling practices are crucial for developing effective AI planning systems that improve patient outcomes and streamline healthcare operations.
6. Financial Management: The costs of AI planning system projects in healthcare are comparable to other AI paradigms. Effective cost management includes leveraging existing resources, adopting modular development approaches, and conducting thorough cost-benefit analyses to ensure financial sustainability.
7. Expertise and Learning: Specialized knowledge in AI planning is not required for all team members, with expertise provided by specialized members. Continuous learning through university courses, research, and expert consultation is essential for maintaining cutting-edge AI planning systems in healthcare.
8. Learning about AI Planning: For healthcare, ensuring AI planning systems remain current with technological advancements involves continuously monitoring recent developments in planning research and implementing them where appropriate. Tools such as Scopus and similar repositories help stay informed about the latest advancements beyond academic research. University-level courses provide valuable learning opportunities for system developers and practitioners

5.2.6 Supply Chain Management Sector

1. Development Process: The development of AI planning systems for supply chain management emphasizes data security, risk assessment, compliance, and efficiency. Tools like Anaplan are used for demand planning, allowing precise forecasting and inventory management.

Constraint programming optimizes production and supply chain logistics, while temporal planning manages detailed scheduling and resource allocation. Optimization algorithms and workflow simulations predict outcomes and manage daily sales orders efficiently.

2. Performance: Effectiveness is measured through KPIs, SLAs, stakeholder feedback, and compliance assessment. Continuous monitoring of performance indicators, system utilization, and error rates ensures reliability and effectiveness. Techniques like load balancing and fault tolerance testing maintain high performance and operational continuity.

3. Interdisciplinary Collaboration: Teams of 8-15 members, including software engineers, data scientists, machine learning engineers, and compliance teams, use agile methodologies to enhance collaboration. "War roomsäre convened for urgent solutions, ensuring swift and effective problem resolution.

4. Technical Challenges: Challenges include server downtime, data load errors, and integrating diverse data sources. Solutions involve creating centralized data hubs, phased integration approaches, and robust API integration. Continuous algorithm optimization and data management strategies ensure accurate and reliable AI planning systems.

5. Data Collection: Data is collected from ERP systems, and logistics distribution systems, and consolidated into a data lake. Multiple dashboards on platforms like PowerBI ensure data accuracy, cleanliness, completeness, and quality, providing a comprehensive overview for modelling tasks.

6. Financial Management: AI planning projects require substantial initial investments. Effective cost management includes careful budget planning, phased implementations, and regular ROI assessments. Capital and operational expenditures are determined by higher leadership, aligning project scopes with business goals.

7. Expertise and Learning: Expertise in AI planning is obtained through formal training, data science and operations specialization, and ongoing professional development. External collaboration is sought for algorithm fine-tuning, parameter optimization, and improving data pipeline structure. Learning opportunities include online courses, development seminars, and practical workshops.

8. Learning about AI Planning: In the supply chain management sector, teams monitor and test new technologies that enhance the existing planning infrastructure. Learning opportunities include various online sources such as LinkedIn, development courses, and practical seminars where AI planning is applied in different industrial contexts

5.2.7 Interdisciplinary AI Planning

1. Development Process: Developing AI planning systems for industrial use adheres to principles of robustness, scalability, and adaptability. Understanding specific industry and user requirements ensures effective system design. Integration involves compatibility checks, modularity, and interoperability using standardized interfaces and protocols. Essential tools and techniques include temporal planning algorithms, heuristic search methods, and probabilistic reasoning. Cloud and distributed computing handle large-scale planning problems efficiently.

2. Performance: Effectiveness is measured through plan quality, execution time, resource utilization, and adaptability to dynamic environments. Extensive testing and validation ensure performance under diverse conditions. Continuous monitoring, error handling mechanisms, and optimization address bottlenecks and inefficiencies. Scalability and reliability are achieved through distributed planning architectures, load balancing, and auto-scaling capabilities.

3. Interdisciplinary Collaboration: Teams typically comprise AI engineers, software developers, domain experts, and data scientists. Collaboration is facilitated through regular meetings, collaborative tools, and joint problem-solving sessions. Planning experts contribute algorithmic insights, while software engineers focus on practical implementation and seamless integration with existing systems.

4. Technical Challenges: Common challenges include scalability limitations, computational complexity, and managing uncertainty in dynamic environments. Solutions involve algorithmic optimizations, parallelization strategies, and integrating probabilistic models. Integrating real-time sensor data for dynamic monitoring and plan adaptation was addressed by developing custom interfaces and algorithms. Thorough root cause analysis and parameter adjustments ensure system reliability.

5. Data Collection: Data collection is crucial for supporting AI planning systems, involving sensors, databases, logs, and user feedback mechanisms. Comprehensive data collection supports continuous refinement and adaptation, ensuring robust and reliable AI planning systems.

6. Financial Management: AI planning system projects incur higher costs due to specialized requirements. Effective cost management includes prioritizing essential features, leveraging open-source tools, and optimizing resource utilization. These strategies ensure financial viability while achieving project goals.

7. Expertise and Learning: Specialized knowledge is acquired through academic study, practical experience, and continuous learning. Expert consultation is sought for complex issues like temporal planning, heuristic search, and probabilistic reasoning. Collaborations with domain experts and researchers provide deep insights into theoretical foundations and practical implementation strategies.

8. Learning about AI Planning: Professionals in interdisciplinary AI planning stay current with technological advancements by regularly attending conferences, workshops, and webinars focused on AI planning, robotics, and related fields. Participation in online forums and communities also helps stay informed about the latest research and developments. Staying updated involves following industry publications, blogs, and newsletters, as well as exploring practical applications and case studies shared by industry practitioners. Numerous learning opportunities are available through online courses, workshops, and training programs offered by universities, professional organizations, and technology companies.

6 Evaluation of the Study

In this chapter, we critically assess the findings of our research by detailing the processes involved in analyzing the collected data and discussing how these data support our conclusions. We explore common best practices in the design, integration, and deployment of AI planning systems, providing a consolidated view of effective strategies. Additionally, we highlight the recurring challenges faced by practitioners, offering insights into the obstacles that need to be addressed to advance the field. Finally, we discuss the implications of our findings for industry practitioners and provide actionable recommendations based on our research. This comprehensive evaluation not only validates our study but also aims to guide future improvements and innovations in AI planning systems.

6.1 Analysis

Following the implementation process outlined in Section 5.1, we began our analysis by examining the findings from our selected group of interviewees. The questionnaire was meticulously structured to focus on key areas essential for creating a fully functioning AI planning system, making it straightforward to identify significant group findings. This analysis is organized into a distribution of group findings, where we extract relevant insights and assess their applicability across different sectors. We aim to determine whether these findings exhibit consistent trends across all sectors or if there are sector-specific dependencies. This structured approach allows us to comprehensively understand the relevance and impact of our findings in various industrial contexts. We will now derive abstract findings by systematically examining each group finding.

6.1.1 Development Process

1. Customer Base: In the aerospace industry, the customer base significantly influences the development of AI planning systems. Given that this customer base primarily consists of highly expensive space programs, it is crucial to tailor each system precisely to meet their specific needs. This high level of customization ensures that the AI planning systems are optimized for these advanced space missions' unique and demanding requirements, thereby maximizing their effectiveness and reliability. The gaming industry places considerable emphasis on the customer base, as the primary goal is to make games increasingly entertaining. This focus shapes the development of AI planning systems to enhance player experience and engagement. However, in other sectors such as healthcare, urban traffic control, robotics, and supply chain management, the customer base does not play as pivotal a role in influencing the development of AI planning systems.

Industry	Customer Base
Aerospace	Expensively funded space programs
Gaming	Players purchasing the game.

Table 6.1: Customer Base

2. Usage of External Tools: In the aerospace sector, the Usage of prominent tools, Tools such as the Monte Carlo search tree, and temporal planning are prominent. In the context of the gaming industry, The tools mentioned before are used in collaboration with algorithms such as HTN planning and the A* algorithm. In the case of Urban traffic control, it heavily relies on PDDL+ for its ability to reason with hybrid discrete-continuous changes. Some subclasses of problems within this domain can also be effectively addressed using temporal planning techniques. Heuristics play a crucial role as well; domain-specific heuristics leveraging Greedy Best-First Search (GBFS) are often developed to optimize planning and decision-making processes. In robotics, For complex decision-making and planning tasks, techniques like Monte Carlo Tree Search (MCTS) are essential, enabling the evaluation of multiple action sequences to optimize outcomes. In interdisciplinary AI planning, The tools mentioned in this section are used in collaboration with cloud computing and distributed systems. In the case of healthcare, the vanilla planner is the most prevalent planning technique. In supply chain management, tools such as Anaplan are commonly used along with temporal planning.

Industry	Tools and Techniques
Aerospace	Monte Carlo Tree Search, Temporal Planning
Gaming	Monte Carlo Tree Search, Temporal Planning, HTN Planning, A* Algorithm
Urban Traffic Control	PDDL+, Temporal Planning, Domain-Specific Heuristics leveraging Greedy Best-First Search (GBFS)
Robotics	Monte Carlo Tree Search (MCTS)
Interdisciplinary AI Planning	Monte Carlo Tree Search, Temporal Planning, HTN Planning, A* Algorithm, Cloud Computing, Distributed Systems
Healthcare	Vanilla Planner
Supply Chain Management	Anaplan, Temporal Planning

Table 6.2: Tools Used for AI Planning

3. Testing Before Deployment: In the aerospace industry, pilot tests are conducted before full-scale deployment to ensure the systems' reliability and functionality. In contrast, game development often lacks such pre-deployment testing phases, relying instead on rapid iterations. In robotics, Extensive testing and iterative feedback loops with the operations team ensure that these integrations enhance functionality without disrupting existing workflows. Simulation software is also critical, allowing for the modeling, testing, and refining of robotic behaviors in virtual environments before actual deployment. This reduces development time and enhances the safety and efficacy of robotic systems. No testing criteria were mentioned

in the Healthcare and interdisciplinary sectors. While in the supply chain sector, rigorous testing was performed to ensure proper integration before deployment. In urban traffic control During deployment, ensuring the performance, reliability, and scalability of the AI planning system under heavy use requires extensive testing.

6.1.2 Performance

1. Real-life Testing: In the aerospace sector, real-life testing and user feedback are integral components of performance evaluation. Similarly, the gaming industry employs this approach, where performance is rigorously tested post-release, with continuous updates provided through in-game patches. In the field of robotics, user feedback is crucial for tracking performance and facilitating necessary updates. Urban traffic control systems are assessed through a combination of historical data comparison and evaluations based on drivers' perceived improvements, ensuring a comprehensive analysis of the system's impact on traffic management. This method of real-life trials, however, is less common in interdisciplinary AI testing. In healthcare, performance is measured by comparing AI outputs against real-life case outcomes, ensuring that the AI system meets practical medical standards. For supply chain management, real-life constraints are applied to evaluate the AI system's performance, ensuring it can handle actual operational challenges effectively.

Industry	**Performance Evaluation Methods**
Aerospace	Real-life testing and user feedback
Gaming	Real-life testing post-release, continuous updates through in-game patches
Robotics	User feedback for tracking performance and updates
Urban Traffic Control	Combination of historical data comparison and Evaluations based on Drivers' perceived improvements
Healthcare	Comparing AI outputs against real-life case outcomes
Supply Chain Management	Application of real-life constraints to evaluate performance

Table 6.3: Performance Evaluation Methods

2. Energy Utilisation: Only present in the aerospace and gaming sector. In the case of NASA's Perseverance Rover, metrics such as energy utilization and the number of planned activities demonstrate the tangible benefits of AI planning systems. In gaming, it is measured by ensuring the system operates within the allotted CPU time budget. This is achieved using CPU profiling tools and telemetry to monitor and optimize performance.
3. Scalability and Reliability: Scalability and reliability are a major performance indicator under heavy stress for all sectors.

6.1.3 Interdisciplinary Collaboration

1. Diverse Professional Backgrounds: A common feature across all sectors utilizing AI planning is the diversity of team members from various professional backgrounds. This multidisciplinary approach is crucial for the successful development and implementation of AI systems. In aerospace engineering, teams typically consist of 5-10 members, with expertise in planning, scheduling, and software engineering. Similarly, in the gaming domain, teams comprise up to 10 individuals, combining diverse skills to enhance game development and AI integration. Urban traffic control teams also consist of around 10 members, featuring a mix of software developers, engineers, and AI experts, ensuring comprehensive system development. In the field of robotics, AI planning teams generally include approximately 15 professionals, encompassing software developers, machine learning experts, and systems integrators to address the complex requirements of robotic systems. Interdisciplinary AI planning necessitates a multidisciplinary team that includes AI engineers, software developers, domain experts, and sometimes data scientists. In healthcare, teams typically range from 5 to 8 members, depending on funding availability, and bring together expertise in planning, software engineering, and data science to develop robust AI planning systems. In supply chain management, team sizes range from 8 to 15 members, comprising professionals such as software engineers, data scientists, data engineers, machine learning engineers, and compliance specialists like MICs and SOX.

Industry	**Team Composition and Size**
Aerospace	Teams typically consist of 5-10 members with expertise in planning, scheduling, and software engineering.
Gaming	Teams comprise up to 10 individuals.
Urban Traffic Control	Teams also consist of around 10 members, featuring a mix of software developers, engineers, and AI experts, ensuring comprehensive system development.
Robotics	AI planning teams generally include approximately 15 professionals, encompassing software developers, machine learning experts, and systems integrators.
Interdisciplinary AI Planning	Multidisciplinary teams include AI engineers, software developers, domain experts, and sometimes data scientists.
Healthcare	Teams typically range from 5 to 8 members.
Supply Chain Management	Team sizes range from 8 to 15 members, comprising professionals such as software engineers, data scientists, data engineers, machine learning engineers, and compliance specialists like MICs and SOX.

Table 6.4: Professional Diversity

6.1.4 Technical Challenges

1. Trust and Acceptance: In aerospace engineering, scientists have been deeply involved in every aspect of planning, often iterating on observation plans for years before execution. The introduction of AI planning systems disrupts this established process, leading to resistance. Scientists may find it difficult to trust AI-generated plans due to their long-standing involvement in manual planning and the traditionally applied detailed scrutiny. Similarly, the healthcare sector follows a similar trend, needing to adhere to multiple clinical guidelines. The usage of PDDL (Planning Domain Definition Language) can significantly influence the acceptance and integration of these guidelines into AI planning systems.
2. Time and Resource Consumption: In the aerospace sector, the planning algorithms require extensive computational resources and time, which can be longer than users find acceptable. In the context of Aerie, the current scheduler needs to perform numerous simulations to effectively build a plan. Each simulation is computationally expensive, resulting in performance issues. In the gaming sector, One occasional technical issue encountered in AI planning systems is unintended backtracking over multiple plan instantiations that have no chance of leading to a successful alternative. This issue is wasteful of CPU time and can significantly impact system performance. In urban traffic control, The most common technical challenge faced while developing the AI planning system is the inability to generate solutions within a given time bound.

Industry	**Input Data Analysis Methods**
Aerospace	Thorough analysis of inputs and processing steps to identify discrepancies.
Gaming	Collaboration with the reporter to understudy the actions that led to the unexpected result.
Robotics	Thorough analysis is conducted to identify the source, typically involving a review of algorithmic decisions and data inputs.
Urban Traffic Control	Fixing the Knowledge Model.
Interdisciplinary AI Planning	Adjusting data parameters depending on the root cause.
Healthcare	Checking for mistakes among the parameters.
Supply Chain Management	Root cause analysis to understand the issue, adjustment of algorithm parameters, and Assessment of input data accuracy and cleanliness. Checking threshold limits and performance metrics of the tool to ensure alignment with expected outputs.

Table 6.5: Input Data Analysis Methods

3. Input Data Analysis: In the aerospace sector, When AI planning systems yield unexpected results, the response involves a thorough analysis of inputs and processing steps to identify discrepancies. The development team, including planners and software engineers, conduct the review sessions to scrutinize the logic and data flow. In the gaming sector, In case, the AI

system produces an unexpected result, there are collaborations with the reporter to understudy the actions that lead to this result. In robotics, When AI planning systems produce unexpected results, a thorough analysis is conducted to identify the source. This typically involves reviewing algorithmic decisions and data inputs. In urban traffic control, the knowledge model is fixed. In interdisciplinary AI, the data parameters may be adjusted depending on the root cause. In healthcare, the team checks for mistakes among the parameters. In supply chain management, In the case where an unexpected result is produced, root cause analysis is performed to understand the issue, there is adjustment of algorithm parameters and close collaboration with data engineers to ensure the data integrity forms the major steps that are taken to resolve the underlying issue. In any other extreme case, collaboration with other teams is also performed. The accuracy and cleanliness of the input data are also assessed, with data engineers responsible for ETL making necessary adjustments to ensure high-quality data loads. Threshold limits and performance metrics of the tool are checked to ensure they align with expected outputs.

6.1.5 Data Collection

1. Usage of Machine Learning: In the aerospace sector, collected data is analyzed using a combination of machine learning algorithms and traditional data processing methods. Machine learning helps uncover patterns and trends that may not be immediately evident, providing deeper insights into system performance and operational efficiency.

2. Usage of sensors: In robotics, Data collection for AI planning systems involves using sensors and cameras on robots to capture real-time operational data. This data is analyzed using AI techniques to refine task performance and identify patterns that can lead to further optimizations. Sensors are also majorly used in interdisciplinary AI planning systems.

3. Usage of Databases and data lakes: In supply chain management, data is primarily collected from various ERP systems and consolidated into a company-managed data lake. This centralized repository allows for efficient data integration and analysis, supporting more informed decision-making processes. In the healthcare sector, data is stored securely, with a strong emphasis on maintaining the privacy of sensitive information. Secure databases and stringent data management practices are essential to protect patient information and comply with regulatory standards. In interdisciplinary AI planning, databases serve as a crucial source of data, integrating information from various domains to support comprehensive AI planning systems. This integration enables the development of more robust and versatile AI solutions.

4. Usage of telemetry: In the gaming sector, The collection of data is performed by gathering the telemetry of various subsystems during the development phase, this, in turn, is shown on a world map of the game in the developers' editor, helping by showing the hot spots in the game.

Industry	Data Collection Methods
Aerospace	Collected data are analyzed using a combination of machine learning algorithms and traditional data processing methods.
Robotics	Data collection for AI planning systems involves using sensors and cameras on robots to capture real-time operational data.
Interdisciplinary AI Planning	Data are collected using sensors and cameras, and databases serve as a crucial source of data.
Supply Chain Management	Data are primarily collected from various ERP systems and consolidated into a company-managed data lake.
Healthcare	Data are stored securely with a strong emphasis on maintaining the privacy of sensitive information.
Gaming	Data collection is performed by gathering the telemetry of various subsystems during the development phase.

Table 6.6: Data Collection Methods

6.1.6 Financial Management

1. Technology Infusion Process: In aerospace, One effective approach used is a technology infusion process. This involves initially allocating a small budget to develop an idea sufficiently to evaluate its potential integration into existing product lines. If this initial phase is successful, the project is then fully budgeted and implemented.
2. Strong retention strategy: In the gaming sector, the primary focus is on maintaining a skilled team of programmers, as it can be more challenging to find engineers who are well-versed in the specific technologies used in AI planning.
3. Staged Development: In robotics sectors, To manage these costs effectively, projects are developed in incremental stages, allowing for early detection of issues and reducing the risk of costly errors. Each stage is validated before further investment, ensuring efficient use of resources. A similar trend is followed in Supply chain management, where Costs are managed by clearly defining project scopes, anticipating potential ROI, and validating benefits at each stage before committing to further investment.
4. Usage of Open source tools: In interdisciplinary AI planning, there is a significant emphasis on utilizing open-source tools to minimize costs. This approach is mirrored in the healthcare sector, where there is a strong focus on leveraging existing resources to keep expenses low. By adopting readily available tools and technologies, both fields aim to achieve cost efficiency while maintaining high standards of functionality and performance.

Industry	**Financial Management Strategies**
Aerospace	Technology Infusion Process.
Gaming	Strong Retention Strategy.
Robotics	Staged Development.
Supply Chain Management	Staged Development.
Interdisciplinary AI Planning	Usage of Open Source Tools.
Healthcare	Usage of Open Source Tools.

Table 6.7: Financial Management Strategies

6.1.7 Expertise In AI planning

1. Collaboration with Universities: In the aerospace sector, Collaborations with universities and research institutions provide access to cutting-edge expertise and facilitate valuable knowledge exchange. In the healthcare sector as well, AI planning experts for collaboration or consultation are often found within the team's university and collaborating universities.
2. Knowledge of AI planning: Knowledge of AI planning, even at a basic level, is deemed crucial for professionals working with AI planning systems. This foundational understanding enables them to effectively contribute to the development, integration, and optimization of these systems, ensuring they can navigate and address the complexities inherent in AI planning.

6.1.8 Learning about AI planning

1. Monetary support: In the aerospace sector The approach followed by experts to keep advancing in AI planning involves proactive communication with program management to secure budgets necessary for staying updated with the latest advancements.
2. Conferences and Research Papers: All sectors enhance their knowledge by participating in research conferences and staying updated with the latest research papers.
3. Development of a Roadmap: In the gaming sector, To ensure that AI planning systems remain current with technological advancements, a development roadmap is maintained that looks ahead by about five years. This forward-thinking approach helps in anticipating future needs and integrating relevant innovations.
4. Monitoring new advances: In Supply chain management, To Keep up with the latest R&D development, some teams monitor and test new technologies that enhance the existing planning infrastructure. In Healthcare, there is a focus on monitoring new advances, This involves continuously monitoring recent developments in planning research and implementing them where appropriate.

Group finding	**Abstract finding**	**Affected Sector**
Development Process	1. Customer base 2. Usage of External tools 3. Testing before Deployment	1. Aerospace and gaming 2. All 3. Aerospace, robotics, supply chain management
Performance	1. Real-life testing 2. Energy utilization 3. Scalability and Reliability	1. Aerospace, Robotics, Urban traffic control, healthcare, Supply chain management 2. Aerospace and gaming 3. All
Interdisciplinary Collaboration	1. Diverse Professional backgrounds	1. All
Technical Challenges	1. Trust and Acceptance 2. Time and resource consumption 3. Input data analysis	1. Aerospace, gaming and healthcare 2. Aerospace, Urban traffic control 3. All
Data collection	1. Usage of machine learning 2. Usage of sensors 3. Usage of Databases and data lakes 4. Usage of telemetry	1. Aerospace 2. Robotics, Interdisciplinary AI planning 3. Supply chain management, healthcare, interdisciplinary AI planning 4. Gaming
Financial Management	1. Technology Infusion Process 2. Strong retention Policy 3. Staged development 4. Usage of open source tools	1. Aerospace 2. Gaming 3. Robotics, Supply chain Management 4. Interdisciplinary AI planning, healthcare
Expertise in AI Planning	1. Collaboration with Universities 2. Knowledge of AI planning	1. Aerospace and healthcare 2. All
Learning about AI planning	1. Monetary Support 2. Conferences and Research Papers 3. Development of Roadmap 4. Monitoring new advances	1. Aerospace 2. All 3. Gaming 4. Supply chain Management and healthcare

Table 6.8: Group Findings, Abstract Findings and Affected Sectors

6.2 Common Best Practices

The following are the common best practices identified in the design, integration, and deployment of these systems:

1. Multidisciplinary Teams: Building successful AI planning systems is a team effort that requires diverse expertise. AI engineers, software developers, domain experts, and data scientists all come together to create systems that are both comprehensive and effective. For example, in fields like aerospace and healthcare, having planners, software engineers, and data scientists work together is crucial for developing AI systems that are both robust and precise.
2. Rigorous Testing and Validation: Making sure these systems perform well under all sorts of conditions means putting them through their paces. This involves a lot of simulations, real-world trials, and continuous performance checks to catch and fix any issues early on. In industries like gaming and robotics, this rigorous testing is essential to ensure the systems can handle the unpredictable nature of their environments while maintaining high performance and reliability.
3. User-Centric Design: It's really important to understand what users need and want from these systems. Getting end-users involved early in the design process helps ensure the final product meets their specific requirements, which boosts acceptance and trust. For instance, in the aerospace sector, there's a lot of interaction with users to make sure the system is transparent and meets their needs. Similarly, in urban traffic control, getting feedback from drivers and other stakeholders is key to making the system more effective.
4. Iterative Feedback and Improvement: These systems get better through continuous feedback. Iterative testing and input from both operational teams and users help refine and enhance functionalities without causing disruptions. This approach is vital both when first deploying the system and for ongoing updates. For example, in healthcare, continuous feedback from medical professionals helps adapt and improve the system based on real-world experiences.
5. Integration with Existing Systems: To work seamlessly, new AI modules need to integrate smoothly with existing software and hardware. This is achieved through custom APIs and middleware, ensuring compatibility and easy communication. Using service-based architectures, like the Fast Downward planner, offers flexibility and makes it easier to integrate advanced AI techniques. In supply chain management, integrating AI planning systems with current ERP systems helps streamline operations and boost efficiency.
6. Scalability and Adaptability: AI planning systems need to be scalable and adaptable to handle increasing workloads and changing conditions. Leveraging cloud computing, distributed planning architectures, and load-balancing mechanisms ensures the system can grow and adapt without needing major redesigns. In robotics and supply chain management, these systems are designed to handle growing complexity and task volumes efficiently.
7. Robust Data Collection and Management: Good data is crucial for these systems to improve continuously. Collecting data from various sources—sensors, databases, user feedback—and managing it properly ensures the system remains accurate and reliable. In urban traffic control, historical data helps assess and improve AI system performance, while in healthcare, clinical practice guidelines and electronic health records are vital data sources.

8. Continuous Learning and Professional Development: Keeping up with the latest technological advancements is key for these teams. Regularly attending conferences, workshops, and training programs helps team members stay updated on the newest research and industry trends. This ongoing learning ensures they can integrate the latest techniques and tools into their work. For example, professionals in aerospace and gaming regularly attend industry-specific conferences to learn about the latest advancements and incorporate them into their systems.

Best Practice	**Brief Explanation**
Multidisciplinary Teams	Building successful AI planning systems is a team effort that requires diverse expertise.
Rigorous Testing and Validation	Ensuring these systems perform well under various conditions means extensive simulations, real-world trials, and continuous performance checks.
User-centric design	Understanding user needs and involving end-users early in the design process helps ensure the final product meets their specific requirements.
Iterative Feedback and Improvement	These systems improve through continuous feedback.
Integration with Existing Systems	To work seamlessly, new AI modules need to integrate smoothly with existing software and hardware.
Scalability and Adaptability	AI planning systems need to be scalable and adaptable to handle increasing workloads and changing conditions.
Robust Data Collection and Management	Collecting data from various sources—sensors, databases, user feedback—and managing it properly ensures the system remains accurate and reliable.
Continuous Learning and Professional Development	Keeping up with the latest technological advancements are key.

Table 6.9: Best Practices

6.3 Recurring Challenges

1. Trust and Acceptance: Getting end-users to trust AI systems can be tough, especially in areas where manual planning has been the standard for years. For instance, scientists in aerospace often struggle to trust AI-generated plans due to their long history with manual planning. Building trust requires extensive user engagement and education to build confidence in these new systems.
2. Algorithm Performance and Computational Resources: AI planning systems can be very demanding in terms of computational resources, leading to performance issues. For example, in aerospace, planning algorithms need numerous simulations to create effective plans, which makes the process resource-intensive and slow. Similar challenges arise in gaming and robotics, where real-time processing is crucial and adds complexity.
3. Unexpected Results and Debugging: AI planning systems can sometimes produce unexpected results, requiring thorough analysis and debugging. This process can be time-consuming and complex, as it involves understanding the underlying logic and data flows. In gaming and robotics, unexpected outcomes can significantly impact performance and user experience, necessitating careful troubleshooting and iterative refinements.
4. Integration with Existing Systems: Integrating AI planning systems with existing software and hardware can be a significant challenge. Custom APIs and middleware are often needed to ensure compatibility and smooth communication between new AI modules and existing systems. This is particularly challenging in supply chain management and urban traffic control, where legacy systems are common.
5. Scalability and Adaptability: Making sure AI planning systems can scale and adapt to changing conditions is crucial but challenging. These systems must handle increasing workloads and dynamic environments without needing major redesigns. This is especially important in healthcare and supply chain management, where scalability and adaptability are essential for managing complex, large-scale operations.
6. Data Collection and Management: Effective data collection and management are critical for the continuous improvement of AI planning systems. However, ensuring the accuracy, cleanliness, and integration of data from various sources is challenging. This is a significant issue in healthcare, where patient data must be handled with great care, and in urban traffic control, where historical and real-time data must be seamlessly integrated.
7. User Training and Knowledge Transfer: Providing adequate training for users to effectively utilize AI planning systems is a recurring challenge. In many sectors, users may not have the technical background needed to fully understand and leverage AI capabilities. Continuous training programs and knowledge transfer initiatives are necessary to address this issue, as seen in aerospace and interdisciplinary AI planning.
8. Financial Constraints: Managing the financial aspects of AI planning system projects can be difficult due to their complexity and the need for cutting-edge technology. Budgeting for initial development, ongoing maintenance, and iterative improvements requires careful financial planning and management. This challenge is common across all sectors, including aerospace, gaming, and supply chain management.

Recurring Challenge	**Brief Explanation**
Trust and Acceptance	Getting end-users to trust AI systems can be tough, especially in areas where manual planning has been the standard for years.
Algorithm Performance and Computational Resources	AI planning systems can be very demanding in terms of computational resources, leading to performance issues.
Unexpected Results and Debugging	AI planning systems can sometimes produce unexpected results, requiring thorough analysis and debugging.
Integration with Existing Systems	Integrating AI planning systems with existing software and hardware can be a significant challenge.
Scalability and Adaptability	Making sure AI planning systems can scale and adapt to changing conditions is crucial but challenging.
Data Collection and Management	Effective data collection and management are critical for the continuous improvement of AI planning systems. However, ensuring the accuracy, cleanliness, and integration of data from various sources is challenging.
User Training and Knowledge Transfer	Providing adequate training for users to effectively utilize AI planning systems is a recurring challenge. In many sectors, users may not have the technical background needed to fully understand and leverage AI capabilities.
Financial Constraints	Managing the financial aspects of AI planning system projects can be difficult due to their complexity and the need for cutting-edge technology.

Table 6.10: Recurring Challenges

6.4 Implication for Industry

1. Need for Multidisciplinary Collaboration: Success in AI planning systems strongly depends on a multidisciplinary team of professionals. It highlights the nature of creating a collaborative work atmosphere between professionals from various domains, including software engineers, data scientists, and others who have domain-specific expertise, to collaborate and collectively solve problems successfully. Members of the profession must, therefore, invest in the establishment of interdisciplinary teams and in facilitating cross-functional knowledge sharing for confronting profound, complex challenges in AI planning system development and deployment.

2. Importance of Trust and User Acceptance: Another critical challenge concerns obtaining the trust and acceptance of end-users. Practitioners need to engage and educate users to build confidence in AI systems. This is how user interest and buy-in would be generated by showing the dependability of and gains to be obtained from pilot projects and concrete examples of using AI planning. By engaging with and addressing the concerns of the users early, practitioners would create a more positive attitude toward AI adoption.

3. Continuous Improvement using Feedback Loops: The iterative feedback and improvement approach form the backbone for continuously enhancing AI planning systems. Building strong feedback loops that reach down to input from end-users and stakeholders can take this forward. This loop of continuous feedback and refinement will identify problems on time and repair them, guaranteeing that the AI system grows according to the changed needs and conditions. Better updated iterations and improvements based on user feedback will lead to more robust and effective solutions for AI planning.

4. Existing System Integration: Smooth integration of AI planning systems with the existing infrastructures calls for effective deployment. Therefore, there is a great need for proper design and development of custom APIs and middleware to enable smooth communication of the new AI modules with existing software and hardware systems. This averts numerous disturbances in everyday operations and maximizes the gain of AI planning. Compatibility and interop also need to be planned from the development stage beginning onward.

5. Scalability and Adaptability: The development of scalable and robust AI planning systems that can adapt to changes is essential. Practitioners should take on flexible system architectures to accommodate increasing workloads and emergent operational requirements. This includes capitalizing on the features of cloud computing, distributed systems, and load-balancing techniques that enable this AI system to be capable, robust, and effective with evolving requirements. Scalable and adaptable systems are essential to sustainable and long-term effective use.

6. Strong Data Management: Successful AI planning systems stand on a practical bedrock of data collection and management. To do this, practitioners should offer advanced data management supported by excellent strategies that will ensure proper accuracy, cleanliness, and integration of data from different sources. Some of these include using advanced data cleansing and integration tools coupled with robust data governance practices. Significant data is therefore required during AI model training to lead to well-performance systems.

7. Financial Planning and Resource Allocation: Financial planning for AI planning system projects helps with efficient budgeting and allocation of all resources. Adequate provision for resources will be necessary for the development, maintenance, and iterative improvements of AI systems. This includes prioritizing essential features, leveraging open-source tools, and seeking external funding or partnerships to offset costs. Financial planning should align with the expected return on investment and operational gains to ensure sustainability.

8. Emphasis on Continuous Learning and Development: Besides, keeping up with technological advancement is crucial to maintaining the relevance of AI planning systems. A requirement for practitioners is to invest in continuous learning and professional development of their teams. This will be achieved through summits, workshops, and ongoing training programs at conference summits. This way, AI systems developed by the practitioner would be up-to-date, cutting-edge, and effective and foster a culture of continuous improvement based on the latest research and trends.

6.5 Recommendations

1. Promote More Cross-Discipline Collaboration: Foster the creation of teams with different skill sets involving AI engineers, software developers, domain experts, and data scientists. This model ensures holistic system design and deals well even with complex challenges. These things are coupled with an ecosystem that supports cross-functional collaboration and learning.

2. Boost Users Engagement and Teaching: Involve the end-users as soon as possible in the development process, and train them thoroughly to build trust and acceptance. Organize workshops, training programs, and pilots to showcase trust in AI planning as explained in the prior stage. Collect user feedback regularly, and apply it to improve the system.

3. Do More Rigorous Testing and Validation: Execute comprehensive testing and validation procedures to guarantee the reliability of AI planning systems across a wide range of operating conditions. Use simulations and field tests to work out and purge any doable bugs before deployment full-scale. Every system requires ongoing performance monitoring and feedback-based iterative improvements need to be made to maintain its effectiveness.

4. Strategy to Build Resilient Integrations: Forge dedicated APIs and middleware, enabling plug-and-play compatibility with existing software & hardware infrastructures of AI planning systems. Replace the new AI modules can better communicate with the existing systems. Minimize disruptions by planning for interoperability from the beginning stages of development.

5. Scalable and Flexible Deployments: Model AI systems appropriately: Design AI planning to scale and evolve with increasing workloads and changing operational requirements. Use cloud computing, distributed system solutions, and load balancing for scalability and efficiency. Systems that scale are systems that stand the test of time, and are effective.

6. Put Advanced Data Management Practices Into Place: Collect relevant, clean, and complete data from disparate sources. Leverage powerful data cleansing and data integration tools for data quality. Appropriate handling of data boosts ongoing performance improvement of plans AI systems and increases system robustness as a whole.

7. Warranted Financial and Resource Allocation: Careful financial Planning and managing of AI planning system projects. Include an initial development budget, ongoing maintenance, and iterative improvements. Put essential features first and look at open source and the opportunities for external funding or partnerships that can help pay the bills.

8. Drive Continuous Learning and Development: Invest in constant professional learning for the team to keep up with the changes in technology. Support attendance to industry conferences, workshops, and training programs. Continual learning guarantees an integration of state-of-the-art skills and methods in the form of AI systems planning.

9. Build Strong Feedback Mechanism: Institutionalize feedback loops to enable end-user and stakeholder input on an ongoing basis. This is useful to quickly identify and solve problems and ensure that the AI system continues to adapt to the demands and conditions. System flexibility and the ability to adapt and iterate quickly based on feedback propel and enhance system resiliency and impact.

Recommendation	**Brief Explanation**
Promote More Cross-Discipline Collaboration	Foster the creation of teams with different skill sets involving AI engineers, software developers, domain experts, and data scientists.
Boost User Engagement and Teaching	Involve the end-users as soon as possible in the development process, and train them thoroughly to build trust and acceptance.
Do More Rigorous Testing and Validation	Execute comprehensive testing and validation procedures to guarantee the reliability of AI planning systems across a wide range of operating conditions.
Strategy to Build Resilient Integrations	Develop dedicated APIs and middleware to enable plug-and-play compatibility with existing software and hardware infrastructures of AI planning systems.
Scalable and Flexible Deployments	Design AI planning systems to scale and evolve with increasing workloads and changing operational requirements.
Put Advanced Data Management Practices Into Place	Collect relevant, clean, and complete data from disparate sources.
Warranted Financial and Resource Allocation	Engage in careful financial planning and management of AI planning system projects.
Drive Continuous Learning and Development	Invest in continuous professional learning for the team to keep up with technological changes.
Build a Strong Feedback Mechanism	Establish feedback loops to enable end-user and stakeholder input on an ongoing basis.

Table 6.11: Recommendations for Enhancing AI Planning Systems

7 Conclusion and Outlook

7.1 Answering our Research Question

Going back to our research question mentioned in 1.2, where the main and most important thing to figure out was what the best practices and challenges faced when developing AI planning systems for engineering were. As already discovered and described in the previous chapter, the best practices across different industrial sectors are diverse professional backgrounds working together, Continuous learning and upgradations, and testing for scalability and resilience to name a few. The recurring challenges identified include managing complexity and scalability, integrating with legacy systems, ensuring performance and reliability, addressing data privacy in the case of medical data, gaining the trust of the scientific community, Unexpected Results, and Debugging.

7.2 Limitation of Our Work

Despite our best efforts, our research, and our desire to get as optimal results as possible, several limitations of our research must be acknowledged as follows:

1. Sample Size and Diversity: The number of respondents is quite informative, but it may not fully represent the diversity of experiences and perspectives across all industries. We reached out to over 70 individuals from various countries, time zones, and industries for participation in the interview. However, we encountered several challenges. Many of the prospective participants did not respond. Additionally, a significant number of those who did reply were unable to participate due to being bound by NDAs, which prevented them from answering our questions. Another common issue was that some respondents had limited or no knowledge of AI planning systems.
2. Scope of Industries: The work focused on a specific scope of industries, and the results would not necessarily be generalizable across all the industries in which AI planning systems are applied.
3. Rapid Changes in Technology: The field of artificial intelligence and technology is rapidly changing; therefore, some findings may quickly become outdated with the emergence of new technologies and methods.
4. Depth of Qualitative Data: While qualitative data can be profound and illuminating, at times, it may lack the breadth that quantitative data can provide.

7.3 Future Work

Given the findings from this study, several areas for future research have been identified, on which this research can be extended.

1. Increasing the Sample Size: Conduct a more extensive survey with more respondents from various industrial areas to cross-check and validate the findings.
2. Longitudinal Studies: Conduct longitudinal studies to analyze how best practices in the field evolve and how problems are encountered in the development of AI technology.
3. Quantitative Analysis: Complement qualitative findings using quantitative data to provide a broader and better overview of implementations of AI planning systems.
4. Enabling Technologies: How emerging technologies such as quantum computing, sophisticated neural networks, and edge AI will impact planning systems.
5. Policy and Ethical Considerations: Exploring the policy implications and ethical considerations of deploying AI planning systems, particularly in terms of data privacy, security, and fairness.

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A

Professional Experience

1. What's your current role, and how long have you been involved with AI planning systems?
Development Process

2. What guiding principles do you follow when developing AI planning systems for industrial use?

3. How do you integrate AI planning systems into your company's existing software architecture? For example, integrating tools like the Fast Downward planner.

4. Which tools, techniques (e.g., Temporal planning, Monte Carlo Tree Search), and technologies are essential for developing AI planning systems in your industry?

Performance

5. How do you assess AI planning systems' effectiveness in real-world industrial applications?

6. What measures do you implement to maintain AI planning systems' performance and reliability during deployment?

7. Can you share practices that ensure AI planning systems are scalable and reliable under heavy use?

Interdisciplinary Collaboration

8. What is the size of the team working with AI planning?

9. Does building systems with AI planning components require expertise in several domains (e.g., planning, software engineering, data science)?

10. How do you facilitate collaboration between people with different backgrounds in an AI planning context? Are there specific interactions between planning experts and software engineers?

Technical Challenges

11. What are the most common technical issues encountered with AI planning systems, and what solutions have you found?

12. Can you describe a major challenge you've faced with AI planning system implementation and how you addressed it?

13. How do you respond when AI planning systems produce unexpected results?

Data Collection

14. How is data collected and analyzed to support AI planning systems?

Financial Management

15. How do the costs of AI planning system projects differ from those of other types of projects, and what strategies can be employed to manage these costs effectively?

Expertise in AI Planning

16. Is specialized knowledge in AI planning required in your role, and how did you acquire it?

17. In which aspects of AI planning is expert consultation most frequently sought? For instance, when dealing with complex planning paradigms like Temporal planning or using specific tools like the Fast Downward planner?

18. Where do you find AI planning experts for collaboration or consultation?

Learning about AI Planning

19. How do you ensure that the AI planning systems you work with stay current with technological advancements?

20. How do you stay informed about the latest developments in AI planning beyond academic research?

21. What opportunities are there for system developers and practitioners to learn about AI planning?

B

Master Thesis Research Interview Preamble: AI Planning Systems in Industrial Applications

Introduction to the Research

For my master's thesis, I am exploring the implementation, challenges, and best practices associated with Artificial Intelligence (AI) Planning Systems across various industrial sectors such as manufacturing, healthcare, robotics, and energy. This investigation aims to gather insights into how AI planning systems are utilized, identify common obstacles, and highlight effective strategies within different industries. This study seeks to:

1. Facilitate a knowledge exchange between the industrial applications of AI planning systems and academic research.
2. luminate industry-wide challenges to steer academic inquiries towards practical, impactful research areas.
3. Support the industry by providing research-driven insights that promote sustainable development and application of AI planning systems.

Confidentiality and Anonymity Guarantee

All information shared during the interviews will remain strictly confidential, accessible only to me and my thesis supervisor(s). Identifiable details will not be disclosed to any third parties without explicit consent from the participants. Data will be presented in an aggregated and anonymized format in the thesis, ensuring that no comments can be linked back to any individual or company. Participants will have the opportunity to review their contributions to adjust or withdraw any information prior to the final analysis. The full transcripts will not be published or disclosed outside the thesis documentation. The data might be published in other documentation for academic purposes, under Proper anonymity and with permissions.

Thesis Interview Procedure and Ethical Considerations

Participants will be briefed on the study's themes beforehand, allowing them to prepare any specific information or insights they wish to share. Interviews are estimated to last between 45 to 60 minutes. With participants' consent, interviews may be recorded for transcription purposes to ensure accuracy and facilitate analysis. Alternatively, if participants prefer not to be recorded or if scheduling challenges arise, questions can be provided in written form, and responses can be submitted at the participant's convenience via email or a secure digital platform. This flexibility aims to accommodate different preferences and schedules, ensuring all participants can contribute meaningfully to this research without the necessity for audio recording. After transcription or receipt of written responses, participants will have the chance to review and approve their contributions, offering a final opportunity to edit or redact any part of their input. Following this approval, audio recordings will be destroyed, and the edited transcript or written responses will form the basis of the qualitative analysis for my thesis.

Purpose of the Study

This research is not intended to evaluate the performance of individuals or to rate companies. It aims to understand the broader applications and challenges of AI planning systems in industry, avoiding the disclosure of any sensitive company-specific information or practices that could impact competitive positioning. Your participation will greatly enrich this study, offering vital insights that can help shape the future of AI planning systems in industrial applications. This project represents an important step in bridging the gap between academia and industry, aiming to enhance both fields through shared knowledge and collaborative research.

Declaration

I hereby declare that the work presented in this thesis is entirely my own and that I did not use any other sources and references than the listed ones. I have marked all direct or indirect statements from other sources contained therein as quotations. Neither this work nor significant parts of it were part of another examination procedure. I have not published this work in whole or in part before. The electronic copy is consistent with all submitted copies.

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place, date, signature