Explainable AI Planning:literature review

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***Abstract*—Explainable AI Planning (XAIP) is a pivotal research area focused on enhancing the transparency, interpretability, and trustworthiness of automated planning systems. This paper provides a comprehensive review of XAIP, emphasizing key techniques for plan explanation, such as contrastive explanations, hierarchical decomposition, and argumentative reasoning frameworks. We explore the critical role of argumentation in justifying planning decisions and address the challenges of replanning in dynamic and uncertain environments, particularly in high-stakes domains like healthcare, autonomous systems, and logistics. Additionally, we discuss the ethical and practical implications of deploying XAIP, highlighting the importance of human-AI collaboration, regulatory compliance, and uncertainty handling. By examining these aspects, this paper aims to provide a detailed understanding of how XAIP can improve the transparency, interpretability, and usability of AI planning systems across various domains.**

INDEX TERMS

Explainable AI, Automated Planning, Argumentation, Replanning, Contrastive Explanations, Human-AI Collaboration, Ethical AI

I. INTRODUCTION

Automated planning is a cornerstone of Artificial Intelligence (AI), enabling systems to generate sequences of actions to achieve specified goals. From robotics to healthcare, planning systems are increasingly deployed in dynamic and uncertain environments. However, as these systems grow in complexity, their decision-making processes often become opaque, limiting their practical utility and user trust. Explainable AI Planning (XAIP) addresses this challenge by providing transparency and interpretability in AI-generated plans, ensuring that users can understand, trust, and effectively collaborate with these systems.

The need for explainability in AI planning arises from several critical factors. First, trust is essential, especially in high-stakes domains like healthcare and autonomous driving. Users must trust AI systems to make reliable decisions, particularly when human lives or significant resources are at stake. For example, in a medical treatment planning system, clinicians need to understand why a specific treatment sequence was recommended to ensure patient safety and compliance. Second, effective human-AI collaboration requires clear explanations to adapt plans to dynamic conditions. In industries such as logistics and manufacturing, human operators must interpret and refine AI-generated plans based on real-time data. For instance, a logistics manager might need to adjust delivery routes due to unexpected traffic conditions, requiring clear explanations of the AI's reasoning. Third, regulatory compliance demands transparent decision-making processes. In sectors like finance and healthcare, AI-driven decisions must be documented and justified to meet legal and ethical standards. Finally, AI planning often involves incomplete or uncertain information, necessitating explanations for risk assessment and error diagnosis. For example, in autonomous driving, explanations of how the system handles sensor uncertainty can improve user confidence and safety.

Explainable AI Planning (XAIP) has been extensively studied, with works like [1] providing a comprehensive review of the field. However, our work offers a novel perspective, focusing on **key techniques for plan explanation**, the role of **argumentation in justifying planning decisions**, and the challenges of **replanning in dynamic environments**.

We present a detailed review of XAIP, exploring methodologies such as **contrastive explanations**, **hierarchical decomposition**, and **argumentative reasoning frameworks**, alongside the **ethical and practical implications** of deploying XAIP in real-world applications. Our goal is to enhance the **transparency**, **interpretability**, and **usability** of AI planning systems across various domains.

II. BACKGROUND

Automated planning systems have become indispensable tools in a wide range of applications, from robotics and healthcare to logistics and autonomous systems. However, as these systems grow in complexity, their decision-making processes often become opaque, limiting their practical utility and user trust. This section provides an overview of the key concepts and challenges related to explainability in AI planning, including the principles of explainability, critical questions in planning, and types of explainability.

A. Principles of Explainability in AI Planning

Explainability in AI planning is grounded in several core principles that ensure transparency, interpretability, and trustworthiness. These principles are essential for making AI-generated plans understandable and actionable for users [2].

- **Transparency**: Planning systems must provide clear and accessible explanations of their decision-making processes. This includes revealing the rationale behind specific actions, the criteria used to evaluate alternatives, and the assumptions underlying the plan [3].

- **Traceability**: Users should be able to trace the sequence of decisions that led to a particular plan. This involves linking actions to their preconditions, effects, and overall goals, enabling users to understand how each step contributes to the final outcome [4].
- **Uncertainty Quantification**: In environments with incomplete or uncertain information, planning systems must explain how uncertainty is handled. This includes providing probabilistic assessments of outcomes and justifying decisions under risk [5].
- **Human-Aligned Justifications**: Explanations should align with human cognitive processes, using terminology and structures that are intuitive and meaningful to users. This ensures that explanations are not only accurate but also actionable [6].

These principles form the foundation of explainable AI Planning (XAIP), enabling users to trust, collaborate with, and effectively utilize AI-generated plans [7].

B. Critical Questions in Explainable Planning

The need for explainability in AI planning raises several critical questions that must be addressed to ensure the successful deployment of these systems in real-world applications. These questions highlight the challenges and opportunities in making planning systems more transparent and interpretable [8].

- **How Can We Build Trust?** Trust is essential, especially in high-stakes domains like healthcare and autonomous driving. Users must have confidence that the system's decisions are reliable and aligned with their goals. For example, in a medical treatment planning system, clinicians need to understand why a specific treatment sequence was recommended to ensure patient safety and compliance [9].
- **How Can We Facilitate Collaboration?** Effective human-AI collaboration requires clear explanations that enable users to adapt plans to dynamic conditions. In industries such as logistics and manufacturing, human operators must interpret and refine AI-generated plans based on real-time data. For instance, a logistics manager might need to adjust delivery routes due to unexpected traffic conditions, requiring clear explanations of the AI's reasoning [10].
- **How Can We Ensure Accountability?** Regulatory compliance demands transparent decision-making processes, particularly in sectors like finance and healthcare. AI-driven decisions must be documented and justified to meet legal and ethical standards. For example, a financial planning system must explain why a specific investment strategy was chosen to comply with regulatory requirements [8].
- **How Can We Handle Uncertainty?** AI planning often involves incomplete or uncertain information, making it essential to understand why certain actions were taken and how they impact overall outcomes. For instance, in autonomous driving, explanations of how the system handles sensor uncertainty can improve user confidence and safety [11].
- **What Are the Ethical Implications?** The deployment of AI planning systems raises important ethical questions, particularly in domains where decisions have significant societal impacts. For example, how should an autonomous vehicle prioritize the safety of its passengers versus pedestrians? How can we ensure that AI-generated plans do not perpetuate biases or inequalities [8]?
- **What Are the Scalability Challenges?** As AI planning systems are applied to larger and more complex problems, scalability becomes a critical concern. Many XAIP techniques require significant computational resources, making them difficult to scale for real-time or large-scale applications [10].
- **How Can We Personalize Explanations?** Different users may require different levels of detail in explanations, depending on their expertise, preferences, and context. For example, a domain expert might prefer technical justifications, while a layperson might need simpler, more intuitive explanations [9].

Addressing these critical questions is essential for advancing the field of Explainable AI Planning and ensuring the successful deployment of AI planning systems across various domains [3].

III. Types of Explainability in XAIP

Explainability in AI planning relies on diverse methodologies, each with unique strengths and limitations, to make AI-generated plans transparent and interpretable. Below, we describe the key types of explainability, their applications, and their implications.

A. Contrastive Explanations

Contrastive explanations aim to answer the question: *Why was this plan chosen instead of another?* They compare the selected plan with alternative plans, highlighting differences in decision criteria such as cost, risk, and efficiency. For example, in a logistics scenario, a contrastive explanation might justify why a specific delivery route was chosen over others based on factors like fuel efficiency and delivery time [12]. This approach helps users understand trade-offs but can be computationally expensive due to the need to generate and evaluate multiple alternatives [13].

B. Hierarchical Explanations

Hierarchical explanations break down complex plans into smaller, more manageable subgoals, making it easier for users to understand and adapt the plan. For instance, in a manufacturing setting, a complex production plan might be decomposed into individual assembly steps, each with its own subgoal [14]. While this approach improves interpretability by simplifying complex plans, it may oversimplify problems and requires domain-specific knowledge to define hierarchical tasks.

C. Argumentation-Based Explanations

Argumentation frameworks provide structured justifications for planning decisions by linking actions to preconditions, effects, and goal dependencies. For example, in a healthcare scenario, a justification graph might show how each treatment step contributes to patient recovery [15]. These frameworks enhance transparency by making the decision-making process traceable but can become computationally intensive in large-scale planning domains.

D. Model Distillation

Model Distillation simplifies complex planning models into human-understandable concepts, making explanations more accessible to non-experts. For instance, a deep learning-based planner might be distilled into a set of rules or decision trees for easier interpretation [16]. However, this method may oversimplify complex models, potentially losing critical information in the process.

E. Interactive Explanations

Interactive explanations allow users to interact with the system, querying specific decisions or exploring alternative plans in real-time. For example, in logistics, a manager might query the system to adjust delivery routes based on real-time traffic data [17]. While this approach enhances user engagement and understanding, it requires significant computational resources and may struggle with scalability in complex domains.

F. Value-Driven Explanations

Value-driven explanations incorporate ethical and regulatory considerations into the explanation process, quantifying trade-offs between competing values such as safety and efficiency. For instance, a medical treatment plan might prioritize patient safety over cost efficiency, with explanations highlighting this value alignment [18]. Although this approach ensures ethical and regulatory compliance, it requires a clear definition of values and their relative importance, which can be subjective.

G. Abductive Explanations

Abductive explanations generate plausible justifications even with incomplete data, ensuring explanatory coherence in uncertain environments. For example, in an autonomous driving scenario, abductive reasoning might infer the most likely cause of a planning failure [19]. While this approach provides coherent explanations in uncertain environments, it may produce speculative explanations that lack empirical support.

Conclusion

By leveraging these types of explainability—particularly **contrastive** and **argumentation-based** approaches—AI planning systems can provide users with the insights they need to understand, trust, and effectively utilize AI-generated plans. In this work, we focus on these two key types of explainability, exploring their potential to enhance transparency and interpretability in AI planning systems.

The table below summarizes the key features of each type of explainability in XAIP, highlighting their strengths and limitations.

TABLE I: Comparison of Explainability Types in XAIP

Type	Description	Advantages	Limitations
Contrastive Explanations	Compares the chosen plan with alternatives to highlight decision criteria.	Helps users understand trade-offs.	Computationally expensive.
Hierarchical Explanations	Breaks down complex plans into smaller subgoals.	Simplifies complex plans.	May oversimplify complex problems.
Argumentation Based Explanations	Provides structured justifications by linking actions to preconditions, effects, and goals.	Enhances transparency and traceability.	Computationally intensive in large-scale domains.
Model Distillation	Simplifies complex models into human-understandable concepts.	Improves accessibility for non-experts.	May oversimplify and lose critical information.
Interactive Explanations	Allows users to query the system and explore alternatives in real-time.	Enhances user engagement and understanding.	Resource-intensive and may struggle with scalability.
Value-Driven Explanations	Incorporates ethical and regulatory considerations into explanations.	Ensures ethical and regulatory compliance.	Requires clear definition of values, which can be subjective.
Abductive Explanations	Generates plausible justifications even with incomplete data.	Provides coherent explanations in uncertain environments.	May produce speculative explanations.

IV. Comparative Analysis of Contrastive Explanations in XAIP

Contrastive explanations are a cornerstone of XAIP, providing users with insights into why a specific plan was chosen over alternatives. This section compares several key studies in the field of contrastive explanations, highlighting their methodologies, contributions, and limitations. By analyzing these works, we aim to provide a comprehensive understanding of the state-of-the-art in contrastive explanations and identify future research directions.

Chakraborti et al. [20] propose a framework for generating contrastive explanations by comparing the chosen plan with a set of alternative plans. Their approach uses a model reconciliation technique to align the user's mental model with the AI's decision-making process. This method introduces the concept of *model reconciliation*, which bridges the gap between user expectations and AI reasoning. However, it requires a predefined set of alternative plans, which may not always be available, and can be computationally expensive for large-scale planning problems. This approach has been applied in healthcare and logistics, where users need to understand why specific decisions were made.

Sreedharan et al. [21] extend the work of Chakraborti et al. by introducing a more efficient algorithm for generating

contrastive explanations. Their approach leverages hierarchical planning to reduce the computational complexity of generating alternative plans. This method improves the scalability of contrastive explanations and provides a more user-friendly interface for exploring alternative plans. However, the hierarchical approach may oversimplify complex planning problems and requires domain-specific knowledge to define hierarchical tasks. This method has been applied in autonomous systems and manufacturing, where hierarchical task structures are common.

Zhang et al. [22] focus on interactive contrastive explanations, allowing users to query the system and explore alternative plans in real-time. Their approach integrates natural language processing (NLP) to make explanations more accessible to non-experts. This method introduces an interactive framework for generating and exploring contrastive explanations, combining formal planning techniques with NLP to improve user understanding. However, the NLP component may introduce errors in complex domains, and the approach requires significant computational resources for real-time interaction. This approach has been applied in logistics and supply chain management, where real-time decision-making is critical.

Vasileiou et al. [23] propose a value-driven approach to contrastive explanations, incorporating ethical and regulatory considerations into the explanation process. Their method quantifies trade-offs between competing values, such as safety and efficiency. This approach integrates ethical frameworks into contrastive explanations, ensuring alignment with societal norms, and provides a formal mechanism for quantifying and comparing values. However, it requires a clear definition of values and their relative importance, which can be subjective, and may not be applicable in domains where ethical considerations are less prominent. This method has been applied in healthcare and finance, where ethical and regulatory compliance is critical.

Kim et al. [24] explore the use of machine learning techniques to generate contrastive explanations. Their approach leverages model distillation to simplify complex planning models into human-understandable concepts. This method combines machine learning with traditional planning techniques to improve explanation quality and provides a scalable framework for generating contrastive explanations in large-scale systems. However, the distillation process may oversimplify complex models, leading to loss of critical information, and requires large amounts of training data for effective model distillation. This approach has been applied in autonomous driving and robotics, where scalability is a key concern.

The studies discussed above demonstrate the diversity of approaches to contrastive explanations in XAIP. While each method has its strengths, they also face common challenges, such as scalability, interpretability, and user-specific requirements. Table II summarizes the key features of these studies.

TABLE II: Comparative Analysis of Contrastive Explanation Methods

Study	Methodology	Strengths	Limitations
chakraborti2017 [20]	Model reconciliation	- Formal framework - Aligns user and AI models	- Computationally expensive
sreedharan2020 [21]	Hierarchical planning	- Scalable - User-friendly	- Oversimplifies complex problems
zhang2019 [22]	Interactive explanations	- Real-time interaction - NLP integration	- Resource-intensive - NLP errors
vasileiou2021 [23]	Value-driven explanations	- Ethical alignment - Value quantification	- Subjective value definitions
kim2021 [24]	Machine learning	- Scalable - Combines ML and planning	- Oversimplification - Data-intensive

V. Explainability Based on Argumentation

Explainability in AI planning has evolved significantly, with argumentation frameworks playing a crucial role in justifying and communicating planning decisions. Early research introduced argumentation as a means to structure decision-making, ensuring that each action taken in a plan could be justified based on logical reasoning. Rahwan and Simari [25] explored the foundations of argumentation in AI, emphasizing its potential in structured reasoning and decision support. Later, Modgil and Caminada [26] proposed a formal account of argumentation, highlighting its capacity to resolve conflicting goals and preferences in planning.

As AI planning systems became more complex, the need for structured justifications grew. Toniolo and Norman [27] demonstrated how argumentation-based decision-making could improve autonomous agent behavior by making their choices more transparent. Around the same time, Fox and Long [28] extended PDDL to handle temporal domains, indirectly contributing to argumentation-based explainability by enabling more detailed reasoning about planning constraints.

Recent research has focused on integrating argumentation with interactive explanations. Fan and Toni [29] introduced a framework where users can query AI systems about planning decisions, receiving structured justifications in return. This approach aligns with Heras and Villata's [30] work, which explored explainable argumentation for human-AI collaboration, emphasizing the importance of user-friendly justifications. Caminada and Podlaszewski [31] advanced this idea further by integrating natural language generation (NLG) techniques, enabling AI planners to present arguments in a way that is more understandable to non-expert users.

Despite these advancements, challenges remain. Bistarelli and Santini [32] discussed the computational cost of structured argumentation, which can become prohibitive in large-scale planning domains. More recently, Cohen and Modgil [33] proposed justification-based argumentation techniques to improve explainability while maintaining computational efficiency. These advancements highlight the ongoing need to balance the interpretability of argumentation-based planning explanations with their scalability in real-world applications.

TABLE III: Comparative Analysis of Argumentation-Based Explainability Methods

Study	Contribution	Strengths	Limitations
Rahwan and Simari (2009) [34]	Foundations of argumentation in AI	- Establishes theoretical foundations - Emphasizes structured reasoning	- Lacks practical implementation details
Modgil and Caminada (2014) [35]	Formal account of argumentation	- Resolves conflicting goals - Provides formal mechanisms	- Computationally intensive
Toniolo and Norman (2015) [36]	Argumentation for autonomous agents	- Improves transparency - Enhances decision-making	- Limited scalability in dynamic environments
Fox and Long (2003) [37]	PDDL extensions for temporal domains	- Enables detailed reasoning - Supports temporal constraints	- Increases complexity of planning models
Fan and Toni (2020) [38]	Interactive argumentation frameworks	- Enables user queries - Provides structured justifications	- Requires significant computational resources
Heras and Villata (2018) [39]	Explainable argumentation for human-AI collaboration	- Focuses on user-friendly justifications - Enhances collaboration	- Limited to specific domains
Caminada and Podlaszewski (2020) [40]	Integration of NLG techniques	- Improves understandability for non-experts - Enhances communication	- May introduce errors in complex domains
Bistarelli and Santini (2022) [41]	Computational cost of structured argumentation	- Highlights scalability challenges - Proposes optimization techniques	- Still computationally expensive
Cohen and Modgil (2021) [42]	Justification-based argumentation	- Improves explainability - Maintains computational efficiency	- Requires further validation in real-world applications

VI. Discussion

The field of Explainable AI Planning (XAIP) has made significant strides in enhancing the transparency, interpretability, and trustworthiness of automated planning systems. This paper has reviewed key methodologies, including **contrastive explanations**, **hierarchical decomposition**, **argumentation-based frameworks**, and **interactive explanations**, highlighting their applications, strengths, and limitations. While these approaches have advanced the state-of-the-art, several challenges remain.

A. Limitations of Current Approaches

- **Scalability**: Many XAIP techniques, such as contrastive explanations and argumentation frameworks, struggle with scalability in large-scale or real-time applications due to their computational complexity.
- **User-Specific Adaptation**: Tailoring explanations to diverse user needs, expertise levels, and contexts remains a challenge, particularly in domains like healthcare and autonomous systems.
- **Ethical and Regulatory Compliance**: While value-driven explanations address ethical considerations, defining and quantifying values in a universally acceptable way is subjective and context-dependent.
- **Uncertainty Handling**: Abductive explanations provide plausible justifications in uncertain environments, but they may produce speculative results that lack empirical support.

B. Future Directions

To address these challenges, future research should focus on:

- **Scalable Algorithms**: Developing more efficient algorithms for generating explanations in real-time and large-scale systems.
- **Personalized Explanations**: Leveraging user modeling and adaptive systems to tailor explanations to individual preferences and expertise.
- **Ethical Frameworks**: Integrating ethical and regulatory considerations into XAIP systems to ensure compliance and societal alignment.
- **Human-AI Collaboration**: Enhancing interactive and collaborative systems to improve user trust and decision-making in dynamic environments.

VII. Conclusion

Explainable AI Planning (XAIP) is a pivotal advancement in making automated planning systems transparent, interpretable, and trustworthy. This paper reviewed key techniques for plan explanation, including contrastive explanations, hierarchical decomposition, and interactive explanations, emphasizing their role in enhancing usability and trust across various domains.

The importance of explainability lies in fostering trust, enabling human-AI collaboration, ensuring regulatory compliance, and managing uncertainty in AI-driven decision-making. Despite progress, challenges such as scalability, user-specific adaptation, and ethical alignment persist. Future research should focus on integrating argumentation with interactive and value-driven explanations to address these challenges, particularly in high-stakes domains.

In conclusion, the future of XAIP lies in bridging technical advancements with user-centric explainability. By advancing argumentation-based approaches, researchers can develop robust, scalable, and ethically aligned systems that empower users and drive the adoption of AI technologies in real-world applications.

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