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Safe and explainable Artificial Intelligence for safety-critical robotic systems

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Abstract

The increasing integration of Artificial Intelligence (AI) into robotic systems introduces both significant potential and critical safety challenges. As many robotic functions rely on opaque, data-driven models, ensuring transparency and trustworthiness has become essential for deployment in real-world environments. Explainable Artificial Intelligence (XAI) has emerged as a key research direction for addressing these challenges. In this work, we systematically examine XAI methods for robotic perception, planning, and control, drawing strong parallels to existing research in autonomous driving (AD). Following the structure of prior surveys, we analyze five major XAI paradigms interpretable-by-design models, interpretable surrogate models, interpretable monitoring, auxiliary explanations, and interpretable safety validation and discuss how each can be applied or extended to robotics. Furthermore, we highlight the limitations of current approaches, especially the fragility and inconsistency of post-hoc explanation techniques such as attention and saliency maps. Building on insights from XAI frameworks for AD, we introduce a modular architecture for robotics that integrates layered explainability with safety monitoring. This survey provides a unified conceptual foundation for developing safe and explainable robotics, offering guidance for researchers, designers, and policymakers seeking trustworthy AI-driven robotic systems.

Keywords: Explainable Artificial Intelligence (XAI); Safe Robotics; Interpretable Models; Human–Robot Interaction

1. Introduction

Artificial intelligence (AI) has become a central component in modern robotic systems, enabling capabilities such as autonomous navigation, perception, manipulation, and human–robot collaboration. As robots operate in increasingly complex and safety-critical environments ranging from autonomous vehicles and service robots to industrial automation, there is a growing demand for transparent, predictable, and trustworthy decision-making processes. This has led to significant interest in Explainable Artificial Intelligence (XAI) for robotics, an area that seeks to make AI reasoning understandable to humans while maintaining system performance (Doshi-Velez & Kim, 2017). Robotics presents unique safety challenges because robots interact with the physical world, where failures can lead to property damage, injuries, or large-scale system hazards. This creates a direct link between explainability and safety assurance. In domains such as autonomous driving, healthcare robotics, and warehouse automation, researchers emphasize that explanations must support debugging, verification, real-time monitoring, accountability, and operator trust (Amodei et al., 2016; Chen et al., 2022). As highlighted in previous reviews focused on autonomous driving, explainability is not merely a technical convenience, it is a functional requirement for safe autonomy, particularly when multiple

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stakeholders rely on AI decisions (Ribeiro et al., 2016). Building on insights from earlier work in explainable autonomous driving, robotics requires explainability at multiple system layers, including perception, planning, and control. For example, perception modules often rely on deep neural networks whose internal operations are opaque, prompting the use of auxiliary explanations such as heatmaps, saliency maps, or segmentation overlays that reveal why a robot focused on certain environmental regions (Sundararajan et al., 2017). At a higher level, interpretable-by-design models such as attention-based architectures, symbolic reasoning components, or hybrid models can approximate black-box behavior while providing human-readable insights into decision logic (Alvarez-Melis & Jaakkola, 2018).

Furthermore, robotics introduces real-time and embodiment constraints not always present in other AI domains. Robots must generate explanations that are timely, context-aware, and actionable for operators, engineers, and end-users. This requires a layered approach to XAI that supports both local explanations (e.g., why the robot chose a particular trajectory) and global explanations (e.g., what rules govern the robot's navigation strategy). This project builds on the foundations and structure of previous studies in explainable autonomous systems while shifting the focus to Safe and Explainable AI in Robotics. The goal is to provide a clear and structured overview of how XAI contributes to robotic safety, the categories of XAI methods used in perception and decision-making, the role of interpretable-by-design algorithms, and remaining challenges in deploying safe, trustworthy robotic systems.

2. Previous Reviews on XAI for Robotics

Research on Explainable AI (XAI) has grown substantially in recent years, and several surveys have examined its application across autonomous systems. However, most existing reviews either focus on general machine learning explainability or concentrate on specific domains such as autonomous driving (AD). While these studies provide valuable insights, they do not fully address the unique constraints and safety considerations present in robotics. This subsection summarizes relevant prior work, compares robotics-oriented reviews to AD-centered surveys, and identifies key gaps that motivate the need for a robotics-focused perspective.

2.1. Existing XAI Surveys in Robotics

Early surveys on XAI for robotics primarily examined how explainability supports human–robot interaction, transparency of robot decision-making, and interpretability of learning-based motion planning. These works highlight the importance of explanations for debugging and improving user trust, particularly when robots operate around humans (Anjomshoae et al., 2019). More recent reviews emphasize explainability in robotic perception and reinforcement learning, noting that deep neural networks used in navigation and manipulation create new opacity challenges that require interpretable models, saliency-based explanations, and attention mechanisms (Brauers & Beetz, 2021).

Overall, robotics reviews converge on several key observations:

- Robots act in embodied, dynamic environments,
- Explanations must support real-time decision-making, and
- Explanations serve multiple stakeholders, including engineers, operators, and end-users.

While these insights are valuable, existing robotics literature remains fragmented across subfields such as perception, lanning, and HRI.

2.2. Comparison with Autonomous-Driving (AD) XAI Reviews

Compared to robotics, autonomous driving has received more structured and comprehensive XAI review efforts. AD-focused surveys provide systematic taxonomies of explainability techniques across perception, prediction, and planning pipelines, often linking them directly to safety and regulatory demands (Hendrikx et al., 2023). These reviews introduce detailed categorizations such as auxiliary explanations (e.g., heatmaps, attention maps), interpretable-by-design architectures, and global vs. local explanations, providing a clearer organizational framework for evaluating XAI methods.

However, while these AD frameworks are technically rich, they are tailored to a single robotic domain road vehicle where sensing modalities, environmental constraints, and decision-making pipelines are relatively standardized. Robotics, in contrast, encompasses diverse platforms (manipulators, drones, service robots, humanoids), each with

distinct safety and explainability requirements. Thus, AD XAI reviews cannot be applied directly to robotics without broader generalization.

2.3. Gaps in Current Literature

Despite ongoing progress, three major gaps remain in existing XAI surveys:

- **Lack of a unified XAI framework for robotics:** Current reviews fragment explainability into isolated components perception, planning, HRI without integrating them into a coherent robotics safety pipeline.
- **Limited focus on safety-driven explainability:** AD reviews strongly emphasize safety justification, risk mitigation, and operational transparency, whereas robotics surveys often underemphasize the direct link between explainability and safety assurance.
- **Insufficient comparison of XAI methods across robotic domains:** There is little cross-domain analysis showing how explainability requirements differ between mobile robots, manipulators, drones, and collaborative robots.
- **Absence of standardized evaluation metrics:** Both robotics and AD surveys acknowledge the difficulty of evaluating explanations, but robotics literature lacks the structured benchmarking methods found in AD research.

2.4. Need for a Robotics-Focused Extension of AD Explainability Research

Because autonomous driving is technically a subset of robotics, AD-focused XAI research provides a strong foundation that can be adapted and expanded. A robotics-focused extension is needed to:

- Address safety challenges across heterogeneous robotic platforms,
- Unify perception, planning, and control explanations into a full-stack transparency framework,
- Incorporate real-time interpretability necessary for dynamic robotic tasks, and align explainability with robotics-specific standards, such as iso 15066 for collaborative safety.

This project responds to these gaps by extending the structured insights from AD XAI literature to the broader domain of safe and explainable robotics, offering a more comprehensive and safety-driven perspective.

3. Foundations of XAI for Robotics

Explainable Artificial Intelligence (XAI) provides the conceptual basis for interpreting how AI-driven robotic systems perceive their environment, make decisions, and execute actions. As robots increasingly operate in dynamic, safety-critical contexts, explainability enables clearer understanding of model behavior, supports verification and validation, and strengthens trust between humans and autonomous systems. Similar to established frameworks in autonomous driving, XAI in robotics can be described through several foundational dimensions that classify how explanations are generated and how they support safe operation (Doshi-Velez & Kim, 2017; Miller, 2019).

3.1. Key Concepts and Taxonomies

One central aspect of XAI for robotics concerns the type of representation underlying a model. Robotic systems may rely on symbolic representations, such as rule-based decision logic or semantic knowledge structures, which are naturally transparent and easy to interpret. Others employ sub-symbolic representations, particularly deep neural networks used in perception and control; these systems achieve high performance but lack inherent interpretability. Hybrid representations combine these two forms, enabling robots to benefit from the expressivity of learned features while still maintaining interpretable high-level reasoning structures (Sucar et al., 2022).

A second dimension concerns the stage at which explanations are produced. Ante-hoc or interpretability-by-design approaches embed transparency directly into the model architecture. These include modular pipelines, attention-based networks whose activations reflect decision relevance, or structured planners whose internal reasoning is explicit and accessible. In contrast, post-hoc explanations are applied after model training and attempt to explain black-box behavior through techniques such as saliency visualization, surrogate modeling, or counterfactual reasoning (Ribeiro et al., 2016). Both stages are relevant for robotics: ante-hoc models support certification and predictable behavior, whereas post-hoc tools help engineers debug opaque perception models. Different modes of explanation further characterize XAI methods. Some approaches employ surrogate models that approximate the behavior of a complex controller with a simpler interpretable model. Others rely on examples or counterexamples to illustrate why a robot chose a particular

action. Importance-based methods attempt to quantify the contribution of specific input features or sensory cues, while inherent explanations arise naturally from models that are intrinsically interpretable, such as symbolic planners or probabilistic graphical models (Lipton, 2018).

The scope of an explanation determines whether it describes the system's behavior for an individual input, for a set of similar situations, or for the model. Local explanations clarify why a robot produced a specific action in a particular instance, such as why a mobile robot chose one trajectory over another. Global explanations describe the overall decision policy governing robotic behavior. Cohort-level explanations fall in between, characterizing model behavior across an entire category of scenarios or environmental conditions (Montavon et al., 2018).

Finally, the medium through which explanations are delivered plays a critical role in robotics. Explanations can be visual, such as heatmaps that highlight salient regions in sensor data; textual, such as natural-language justifications of decisions; or even tactile or haptic feedback in human–robot collaboration settings. The choice of medium depends on the operational context and the needs of the intended user.

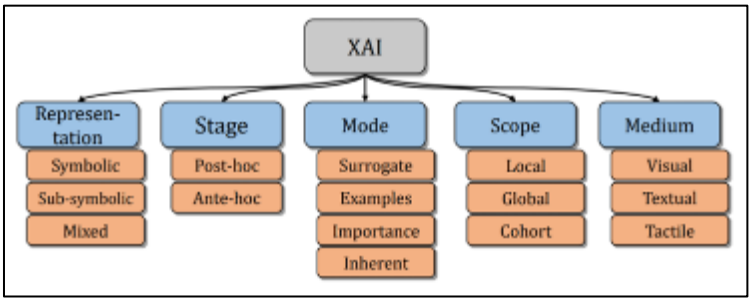

Figure 1 Taxonomy of XAI Diagram

3.2. Stakeholders and Requirements

Robotic systems serve a diverse set of stakeholders, each with different expectations for explainability. Operators who interact with robots in real time, such as technicians or human collaborators on manufacturing floors, require clear and timely explanations that help them anticipate robot behavior and intervene when necessary. Engineers and developers rely on deeper, technically detailed explanations that support debugging, optimization, and model verification. Regulators and safety auditors require explanations that justify compliance with safety standards and demonstrate that the system behaves predictably under varying environmental conditions. End-users, including non-experts, often need intuitive, high-level explanations that build trust without overwhelming them with technical detail (Anjomshoae et al., 2019).

The relationship between explainability, safety, and trust is foundational in robotics. Transparent reasoning enables stakeholders to detect failures, identify unsafe behaviors, and understand system limitations. In high-risk applications such as surgical robotics, autonomous drones, and collaborative industrial robots, the absence of explainability can hinder certification processes and reduce human willingness to rely on autonomy. Effective XAI therefore enhances both operational transparency and system dependability, ultimately contributing to safer robotic deployment across diverse environments.

4. XAI Design Paradigms Applied to Robotics

Research on explainable artificial intelligence in robotics can be organized into several design paradigms that parallel those used in autonomous driving literature. These paradigms represent different strategies for generating, structuring, or validating explanations, and each plays a distinct role in supporting safe robotic operation. By extending the conceptual structure developed for autonomous driving to the broader robotics domain, we gain a unified lens through which to analyze interpretability methods across perception, planning, and control. The following subsections outline five major paradigms: interpretable-by-design models, surrogate explanations, interpretable monitoring, auxiliary explanations, and interpretable safety validation and discuss their relevance, benefits, and limitations for robotics.

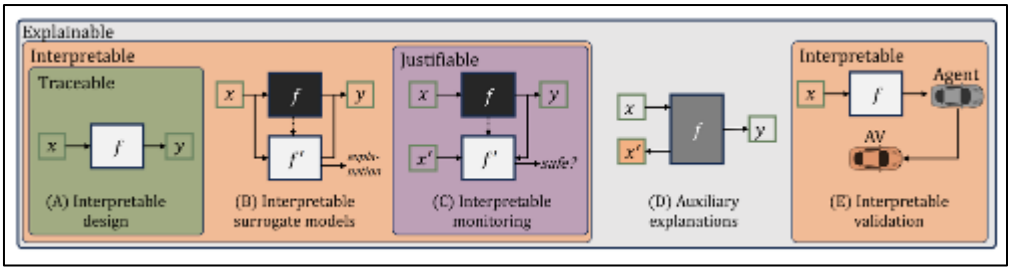

Figure 2 Categories of XAI Methods

4.1. Interpretable-by-Design Models

Interpretable-by-design models aim to embed transparency directly into the architecture of the robotic system. These approaches rely on representations that are inherently understandable, such as symbolic reasoning systems, decision trees, rule-based controllers, and concept bottleneck models. For instance, symbolic planners have historically been used to generate explicit task plans for manipulation and navigation, allowing users to trace the reasoning steps that lead to a robotic action. Similarly, concept bottleneck architectures constrain neural networks to predict intermediate, human-understandable concepts such as object affordances, grasp stability, or collision risk before producing final outputs (Koh et al., 2020).

The primary advantage of such models in robotics is their traceability. Engineers can inspect each decision step, determine why a particular action was chosen, and verify that the robot's internal logic aligns with safety requirements. These properties are especially important in applications such as collaborative industrial robotics and medical robotics, where certification and regulatory approval depend on demonstrable system transparency (Fitzgerald & Hall, 2021). However, interpretable-by-design methods may struggle to match the performance of deep learning systems in complex perception tasks, limiting their application to carefully structured domains.

4.2. Interpretable Surrogate Models

Interpretable surrogate models attempt to approximate the behavior of more complex, black-box robotic policies by constructing simplified, human-readable models. Examples include rule extraction from deep reinforcement learning policies, local linear models used to approximate robotic motion decisions, and interpretable regressors that estimate the importance of sensory inputs (Ribeiro et al., 2016). Shapley-based methods are also used to quantify how individual features contribute to a robot's control output or object recognition decision (Lundberg & Lee, 2017). While surrogate models provide useful insights for debugging robotic systems, they suffer from inherent limitations. Because they attempt to mimic rather than directly represent the underlying policy, surrogate explanations may lack faithfulness and can oversimplify the system's true behavior. This mismatch poses safety risks if engineers mistakenly rely on approximate explanations to validate critical robotic functions. As noted in prior autonomous-driving research, the interpretability faithfulness tradeoff becomes particularly problematic in scenarios involving complex, high-dimensional sensor data, a challenge shared by robotics in general.

4.3. Interpretable Monitoring

Interpretable monitoring offers an alternative paradigm in which the focus is not on explaining the model itself but on supervising robotic behavior during operation. Runtime monitors evaluate whether robot actions conform to predefined safety rules, often implemented through interpretable logic-based specifications. These systems can detect unsafe deviations from expected behavior, trigger corrective actions, or intervene to prevent failures (Dahl et al., 2022). For instance, a robot manipulator may use safety filters to prevent joint trajectories from violating collision constraints, while mobile robots employ interpretable policy checks to ensure navigation remains within safe operational boundaries.

This paradigm parallels monitoring techniques used in autonomous driving, where runtime safety layers continuously verify the validity of a vehicle's actions. In robotics, interpretable monitoring is particularly valuable because robots operate in environments with unpredictable human behavior, requiring real-time verification that is both transparent and actionable. The clarity of these monitoring rules supports certification processes and facilitates human oversight.

4.4. Auxiliary Explanations

Auxiliary explanations constitute one of the most widely used classes of XAI methods in robotic perception. These techniques generate explanatory artifacts that accompany the outputs of a robot's perception or decision-making system. Heatmaps are common examples, highlighting regions of an image or point cloud that most influenced a classification or control output. Similarly, attention maps produced by transformer-based models indicate which spatial or temporal features shaped a prediction, making them especially useful for understanding robotic scene interpretation, grasp selection, or trajectory prediction.

Despite their popularity, auxiliary explanations face significant challenges. Saliency methods are known to be fragile and inconsistent across different inputs, architectures, and training conditions (Adebayo et al., 2018). In robotics, this inconsistency is particularly problematic because explanations must support safety-critical interpretation; an incorrect heatmap can mislead engineers into believing that a perception module focuses on relevant features when it does not. Moreover, auxiliary explanations rarely provide causal guarantees, meaning they depict correlations rather than definitive reasons behind robotic decisions. Their limited reliability underscores the need for complementary or more principled interpretability methods, especially in high-risk applications.

4.5. Interpretable Safety Validation

The final paradigm involves using interpretable methods to validate robotic behavior through formal or semi-formal safety frameworks. Temporal logic specifications such as Signal Temporal Logic (STL) and its probabilistic variants are increasingly used to express safety requirements over time and to ensure that robotic trajectories satisfy these constraints (Raman et al., 2014). These logic-based specifications are inherently interpretable, allowing engineers to clearly articulate rules such as maintaining safe distances, enforcing stability under disturbances, or ensuring successful task completion.

In addition to verification, interpretable safety validation also includes scenario extraction and adversarial test generation, which help identify failure conditions that a robot may encounter. These methods parallel safety validation processes in autonomous driving, where explainability is used to organize and evaluate scenario-based testing. Extending such frameworks to robotics supports systematic identification of unsafe behaviors and enhances the transparency of the validation pipeline. In safety-critical settings, interpretable validation techniques serve as essential tools for certifying the dependability of autonomous systems.

5. Explainability Across the Robotics Stack

Explainability requirements in robotics span the full autonomy pipeline from perception to planning and control. Each layer presents unique challenges due to heterogeneous sensor modalities, task variability, and real-time safety demands. As in autonomous driving research, different components of the robotics stack require different forms of explanations, raising questions about faithfulness, robustness, and usability for operators and engineers (Adebayo et al., 2018; Ribeiro et al., 2016).

5.1. Perception Systems

Perception is one of the most complex and opaque components in robotic autonomy. Robots rely on high-dimensional sensory inputs. RGB cameras, depth sensors, LiDAR, tactile arrays, and multimodal sensor-fusion pipelines to interpret their environment. XAI work in this domain predominantly focuses on visual interpretability, following similar trends to autonomous driving, where heat maps and saliency-based methods are used to highlight input regions that most strongly influence the model's predictions (Adebayo et al., 2018).

Intermediate feature visualization, attention maps, and Class Activation Mapping (CAM) style techniques attempt to expose internal representations of perception modules. However, these methods often suffer from fragility, lack of causal grounding, and high sensitivity to model randomization, raising questions about reliability in safety-critical robotic applications. Evaluation remains a persistent challenge: visual explanations may appear plausible to humans yet fail to reflect the true reasoning process of the underlying model, a problem well-documented in both robotics and autonomous driving literature.

Sensor fusion introduces an additional layer of complexity. When perception relies on heterogeneous modalities (e.g., fusing LiDAR and vision), explanations must clarify not only the importance of individual features but also how

multimodal signals interact to produce predictions. Current research shows that these explanations frequently fail to capture cross-modal dependencies, creating gaps in transparency for robotic perception systems.

5.2. Planning and Prediction

Planning and prediction modules transform processed sensory information into high-level decisions such as navigation trajectories, human–robot interaction behaviors, or manipulation strategies. Explainability in this layer is essential for both debugging and operator trust. In robotics, several approaches attempt to make planners more intelligible by producing graphical or textual rationales for why a robot selected a particular trajectory, pose, or grasp configuration.

One common technique is to visualize predicted trajectories or goal-conditioned behaviors, allowing operators to see the reasoning behind route selection or action sequencing. Example-based explanations, such as retrieving past similar situations, are also used to justify decisions in dynamic or partially observable environments.

More structured approaches rely on cognitive or hierarchical planning frameworks, in which symbolic reasoning is layered above learned modules to provide interpretable intermediate decisions (Fitzgerald & Hall, 2021). Surrogate models are also used to approximate complex planning policies, translating them into rules or decision trees to expose high-level abstractions. Although these surrogates can make planning behavior more comprehensible, they inherit the same limitation found in autonomous driving: reduced fidelity to the true underlying model, which raises concerns about faithfulness.

5.3. Robotic Control

Explainability in robotic control remains one of the least explored areas, mirroring the gaps observed in autonomous driving. Many modern robotic controllers especially those trained using reinforcement learning (RL) contain deep neural architectures that are inherently opaque. As robots increasingly rely on RL for dexterous manipulation, locomotion, and adaptive behavior, the need for transparent control logic becomes more pressing.

Several emerging methods attempt to bridge this gap. Projection mechanisms map latent policy representations into simplified interpretable spaces, allowing operators to inspect how controllers respond to environmental variations. Other approaches use symbolic abstractions or temporal logic constraints to create human-interpretable summaries of controller behavior (Raman et al., 2014).

Despite these efforts, explainable control remains significantly underdeveloped. Unlike perception or planning, there are few standardized benchmarks, and controlling explanations often struggle to remain robust under real-time constraints. As robotics systems expand into safety-critical domains healthcare, manufacturing, aerial robotics, the absence of mature XAI techniques for control presents a substantial risk. Advancing explainability at this layer is therefore a crucial research frontier for safe autonomous robotics.

6. A Unified Framework for Safe and Explainable Robotics

To operationalize explainability as a core safety mechanism in robotics, we propose a unified framework that integrates interpretable models, monitoring components, and multi-layered defense mechanisms across the robotic autonomy stack. Similar to safety-oriented XAI frameworks in autonomous driving, this framework treats explainability not merely as a post-hoc descriptive tool but as an active component of system assurance. The goal is to ensure that robots remain transparent, predictable, and verifiably safe in dynamic and uncertain environments.

The framework consists of three interconnected elements: an Explainable Monitoring System (EMS), module-level integration of XAI techniques across perception, planning, and control, and a layered “Swiss cheese” safety architecture that embeds redundancy into the explainability pipeline (Dahl et al., 2022; Raman et al., 2014).

6.1. Explainable Monitoring System (EMS)

The Explainable Monitoring System (EMS) functions as the central bridge between the robot and human stakeholders. It observes the robot’s decisions, checks them against safety and performance constraints, and produces explanations that translate internal model states into intelligible outputs. The EMS serves two simultaneous purposes: real-time safety assurance and human-facing explanation delivery. For safety, the EMS performs continuous validation of robot behavior, including trajectory deviations, anomalous sensor readings, or violations of learned or symbolic rules. These

checks may rely on interpretable safety monitors, runtime temporal logic validators, or simple symbolic constraints that can override unsafe decisions when necessary (Dahl et al., 2022). For explanation delivery, the EMS provides concise, actionable summaries of why the robot selected a specific action, highlighting relevant sensory cues, predicted outcomes, or constraint activations. This design positions the EMS as a mediation layer, simultaneously guarding against unsafe behaviors and enhancing transparency for operators, engineers, or end-users.

6.2. Module-Level Integration

A unified safe-XAI framework must embed interpretability at multiple points within the robotics pipeline rather than isolating it as a separate external module. At the perception level, auxiliary explanations such as saliency maps or feature visualizations help clarify why the robot identifies objects, obstacles, or affordances in a particular way. These are complemented by ante-hoc interpretable models such as concept bottleneck architectures that structure perception around human-meaningful concepts (Koh et al., 2020). Within planning and prediction, surrogate models can approximate complex neural planners and provide symbolic or rule-based summaries of decision logic. For example, a deep navigation model may be shadowed by a decision tree that exposes high-level route selection principles. In safety-critical robotic manipulation, interpretable grasp planners or cognitive symbolic planners offer additional transparency into task sequencing and goal prioritization (Fitzgerald & Hall, 2021).

At the control layer, interpretable reinforcement learning controllers or temporal-logic-guided controllers enable explanations of low-level actuation policies. Although still an emerging research area, control-level explainability is essential for diagnosing unsafe control strategies and ensuring predictable robot motion (Raman et al., 2014). Module-level integration thus creates a multi-pronged interpretability structure: inherent models for transparency, surrogates for approximating complex policies, and auxiliary explanations for visual and feature-level introspection. Together, these components ensure that each stage of the autonomy pipeline contributes to overall system safety.

6.3. Layered ("Swiss Cheese") Safety Model

To further enhance robustness, the unified framework adopts a layered "Swiss cheese" model, where multiple explainability components serve as overlapping safety filters. Rather than relying on any single XAI method which may fail due to fragility, approximation errors, or sensor noise, the system deploys diverse interpretability mechanisms across perception, planning, and control.

For instance, perception may utilize both saliency-based explanations and symbolic concept bottlenecks, reducing dependence on one form of interpretability. Planning modules may combine rule-extracted surrogates with visualized trajectory rationales. Control systems may integrate constraint-based safety monitors alongside interpretable RL projections. When one method fails or becomes unreliable, another layer provides redundancy, maintaining safe operation. Additionally, fallback safety mechanisms such as emergency stops, override constraints, or high-level symbolic validators ensure that the system can intervene decisively when explanations indicate potential hazards. These redundant layers create a safety net that prevents cascading failures and provides consistent transparency, enabling operators to detect anomalies early and intervene when needed.

Overall, this layered approach transforms explainability from a descriptive afterthought into a functional safety mechanism. The combination of EMS, module-level XAI integration, and multi-layered redundancy offers a holistic blueprint for safe and transparent robotic autonomy.

7. Discussion

Although explainable artificial intelligence has advanced rapidly in robotics, progress across the autonomy stack remains uneven. Perception has received the most attention, largely because visual deep-learning models are notoriously opaque and because heat maps, attention visualizations, and feature-based explanations are comparatively easy to generate. However, this focus has created a research imbalance. Planning and control arguably the components with the most direct impact on safety lag significantly behind perception in both methodological development and empirical evaluation. As a result, robots often provide detailed visual explanations of what they "see" but far fewer insights into why they choose actions or how control policies translate decisions into motion. The limitations of attention and saliency-based approaches further exacerbate this imbalance. While widely used, these methods offer only partial and sometimes misleading approximations of model reasoning, and their vulnerability to model randomization raises questions about their reliability in safety-critical robotics (Adebayo et al., 2018). Their dominance in the XAI landscape has also constrained innovation, overshadowing alternative interpretability paradigms that may offer stronger causal grounding or more faithful introspection.

Another critical gap is the lack of multimodal explainability. Robotic perception extends far beyond RGB inputs, relying on LiDAR, radar, proprioception, force–torque sensing, and tactile feedback. Yet most current XAI research remains heavily vision centric. Effective explanations for multimodal sensor fusion remain underdeveloped, even though safe operation often depends on correctly integrating diverse sensory streams. Without robust multimodal XAI, failures in non-visual sensors may remain opaque to operators, undermining overall safety. User-centered evaluation is also limited. Robotics systems interact with a wide range of stakeholder's operators, technicians, supervisors, end-users, and regulators each of whom has different expectations and cognitive needs. Nevertheless, most XAI evaluations rely on developer-centered benchmarks or synthetic tasks that fail to capture the interpretability requirements of real users. Understanding how explanations support decision-making, trust calibration, and error prevention in practical robotic settings an urgent research priority is therefore.

Finally, generative models are emerging as a major influence on robotic autonomy. Large multimodal models now support scene understanding, policy generation, and simulation-based training. Their integration introduces new opportunities for interpretable reasoning such as natural language rationales for example-based counterfactuals but also new risks, including hallucination, distributional drift, and complex failure modes that challenge existing XAI tools. As robotics moves toward foundation-model-driven autonomy, interpretability research must adapt to ensure that generative systems remain safe, transparent, and verifiable.

8. Conclusion

This paper has surveyed core approaches to explainable AI in robotics across perception, planning, and control, highlighting how interpretability can support safety, transparency, and operator trust. We analyzed interpretable-by-design models, surrogate-based approaches, monitoring systems, auxiliary perceptual explanations, and formal safety-validation techniques, emphasizing how each contributes to understanding and regulating robotic behavior. By examining explainability across the full autonomy stack, the survey reveals a fragmented but rapidly evolving landscape in which different XAI methods address different failure modes and stakeholder needs. To unify these diverse strands, we introduced a layered framework for safe and explainable robotics. This architecture combines real-time monitoring, integrated module-level interpretability, and redundant safety layers to create a resilient explainability pipeline. Rather than treating explanations as optional, the framework embeds them as active safety mechanisms that mediate between robot decision processes and human operators.

Looking forward, a central challenge will be developing multimodal XAI methods that extend beyond vision to encompass LiDAR, tactile, auditory, and proprioceptive inputs. Equal emphasis must be placed on planning and control, where interpretability is still underexplored despite its importance for safe physical interaction. As generative models reshape robotics, grounding explanations in verifiable reasoning will become increasingly essential. Advancing these directions will be critical for creating robotic AI systems that are not only intelligent but also trustworthy, transparent, and aligned with human safety expectations.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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