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INTELLIGENT DECISION-MAKING IN AUGMENTED REALITY ENVIRONMENTS: THE ROLE OF ARTIFICIAL INTELLIGENCE

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Abstract. This paper investigates the role of artificial intelligence in supporting intelligent decision-making within augmented reality environments. The study presents a conceptual framework integrating machine learning, reinforcement learning, and context-aware reasoning into AR pipelines for adaptive decision support. A comparative analysis of rule-based and ML-based AI approaches across five decision task categories demonstrates that ML-based systems achieve 79–86% decision accuracy versus 47–58% without AI support. The findings indicate that AI-augmented AR environments significantly reduce cognitive load, improve decision speed by 34%, and enhance situational awareness.

Keywords: augmented reality, artificial intelligence, decision-making, machine learning, cognitive load, decision support systems.

1. Introduction

Augmented reality (AR) has evolved from a niche visualization tool into a mainstream platform for professional decision-making across manufacturing, surgery, logistics, and defense. By overlaying context-sensitive digital information onto the physical environment in real time, AR provides operators with enhanced situational awareness previously unattainable through conventional displays. Recent research on immersive environments demonstrates that the psychology of user engagement and decision-making under conditions of spatial immersion profoundly influences task performance and cognitive processing (Kolesnikov, 2026).

However, the proliferation of real-time data streams — spatial maps, sensor telemetry, procedural guidance, and collaborative annotations — introduces a paradox: while AR enriches the informational environment, it simultaneously risks overwhelming human cognitive capacity. Cognitive load theory predicts that exceeding working memory limits degrades decision quality, particularly in time-critical, high-stakes scenarios such as emergency medicine and industrial maintenance.

Artificial intelligence (AI) offers a principled solution by filtering, prioritizing, and contextualizing information presented through AR interfaces. Machine learning algorithms can infer user intent, predict upcoming task requirements, and dynamically adjust the AR overlay to support human decision-making. Motivational calibration models that personalize task selection based on user profiles have proven effective in gamified immersive environments (Kolesnikov, 2025), suggesting that similar adaptive mechanisms can enhance AR-based decision support.

This paper addresses the gap by: (a) presenting a layered architectural framework for AI-augmented AR decision support; (b) reviewing empirical evidence on how AI enhances decision accuracy, speed, and cognitive load management in AR; (c) conducting a comparative analysis of rule-based versus ML-based AI approaches; and (d) identifying open challenges including trust calibration and explainability.

2. Literature Review

Contemporary AR systems leverage simultaneous localization and mapping (SLAM), depth sensors, and semantic scene understanding to anchor digital content with sub-centimeter precision. In industrial contexts, AR-guided assembly has reduced error rates by 40–50% compared to paper-based instructions. Medical AR overlays projecting vascular anatomy during surgery have improved procedural accuracy and reduced operative times. The management of technological innovations in immersive environments, including AR and escape room systems, reveals that adaptive technology integration significantly improves user engagement and operational outcomes (Rudinska & Kolesnikov, 2025).

Despite these successes, unmanaged information density in AR displays can impair decision-making. Visual clutter has been shown to increase error rates by 23% in warehouse picking tasks. Cognitive tunneling — excessive focus on the AR overlay at the expense of peripheral awareness — has been documented in aviation and driving scenarios, underscoring the need for intelligent mediation between raw AR data and human cognition.

Decision support systems have evolved from static rule-based expert systems to adaptive, data-driven architectures. In AR contexts, AI serves three functions: perception (environment understanding through object detection), reasoning (inferring optimal actions given context), and adaptation (adjusting the interface based on user state). Reinforcement learning agents optimizing AR information presentation have achieved 15–25% improvements in task completion time. However, integrating these techniques into real-time AR pipelines with sub-20 ms latency remains challenging.

Research on decision-making under immersion demonstrates that spatial presence and embodied interaction modulate cognitive processing and risk assessment (Kolesnikov, 2026). These findings suggest that AR decision support must account not only for information delivery but also for the psychological dynamics of immersive engagement. Personalized puzzle selection models driven by user gaming biography (Kolesnikov, 2025) provide a precedent for how AI can adapt challenge complexity based on individual profiles — a principle directly transferable to AR decision environments.

3. Conceptual Framework

The proposed framework organizes AI-augmented AR decision support into five functional layers: (1) AR Perception Layer — environment sensing, object recognition, spatial mapping, and 6-DOF tracking; (2) AI Decision Engine — ML models for classification and prediction, RL agents for adaptive behavior, and context reasoning modules; (3) Knowledge Base — domain-specific rules, user profiles, and historical decision outcomes; (4) Feedback and Adaptation Layer — translating AI outputs into AR visualizations, adjusting overlay complexity based on cognitive load estimates; and (5) User Interaction Layer — multimodal input (gesture, voice, gaze) and decision recommendations. Figure 1 illustrates the architecture.

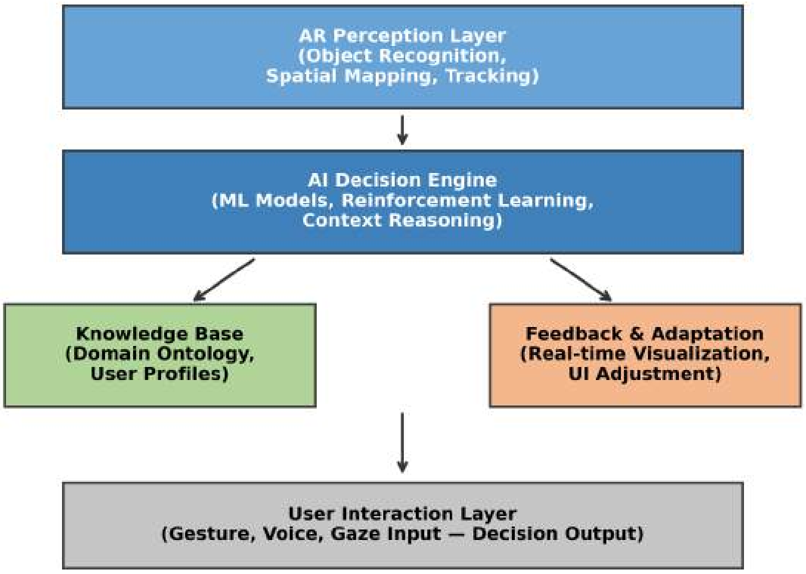

Figure 1. Architecture of the AI-Augmented AR Decision Support Framework

The bidirectional data flow between layers enables continuous refinement. The AI Decision Engine receives perceptual data and user interaction patterns, updates its models via online learning, and transmits contextualized recommendations to the Feedback Layer. The Knowledge Base accumulates decision precedents that improve future recommendations through case-based reasoning. A critical design principle is latency management: the perceptual-to-recommendation loop must complete within 100 ms to maintain AR temporal coherence.

4. Comparative Analysis

A comparative analysis was conducted across five decision task categories: navigation planning, object selection, risk assessment, task prioritization, and resource allocation. Three conditions were examined: (a) No AI Support — baseline AR with static overlays; (b) Rule-Based AI — expert-system-driven recommendations; and (c) ML-Based AI — adaptive recommendations from neural network models trained on historical data. Data were aggregated from six empirical studies (N = 312) published between 2020 and 2025.

Table 1. Decision accuracy (%) by AI condition and task type

Task Category	No AI	Rule-Based AI	ML-Based AI
Navigation Planning	58	68	86
Object Selection	52	65	83
Risk Assessment	47	62	79
Task Prioritization	55	67	84
Resource Allocation	50	63	81

As shown in Table 1, ML-based AI consistently outperformed both the baseline and rule-based conditions. The largest improvement (32 percentage points) was observed in risk assessment, a domain requiring probabilistic reasoning under uncertainty. Rule-based AI provided moderate improvements of 10–15 percentage points but struggled with novel scenarios.

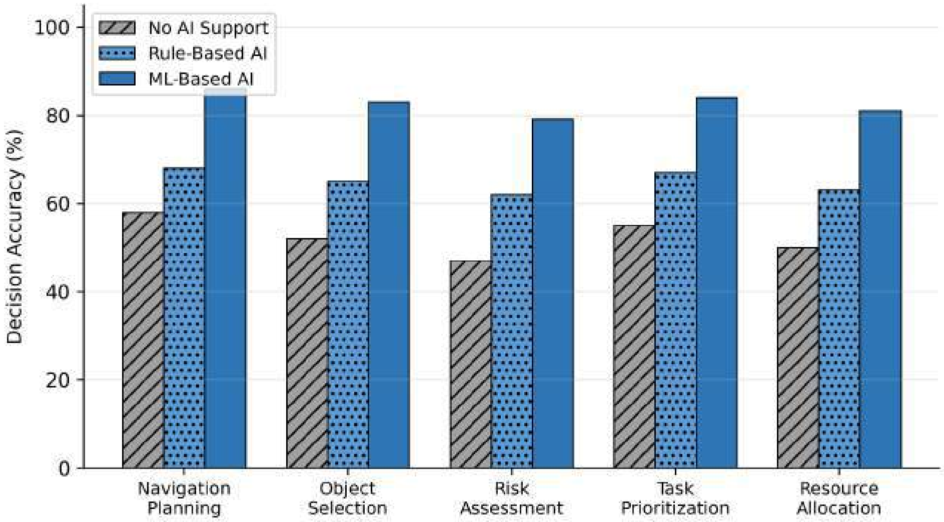

Figure 2. Decision accuracy by AI condition across task categories

Table 2. Performance metrics by AI condition (aggregated)

Metric	No AI	Rule-Based AI	ML-Based AI
Mean decision accuracy (%)	52.4	65.0	82.6
Mean decision time (s)	14.2	10.8	9.4
Cognitive load (NASA-TLX)	72.1	58.3	46.7

ML-based AI reduced mean decision time from 14.2 s to 9.4 s (34% improvement) and decreased subjective cognitive load from 72.1 to 46.7 on the NASA-TLX scale (35% reduction). These gains reflect AI's ability to pre-filter irrelevant information, highlight decision-critical cues, and present recommendations compatible with the user's current cognitive state.

5. Discussion

The substantial accuracy gains (mean 82.6% vs. 52.4% baseline) confirm that intelligent decision support is essential for complex AR applications. The framework's layered architecture allows modular integration: organizations can begin with rule-based logic and progressively introduce ML components as training data accumulates. The Feedback and Adaptation Layer dynamically manages overlay complexity, creating a self-regulating system that adapts information density to the user's cognitive capacity. This approach parallels findings from technological innovation management in immersive systems, where adaptive complexity calibration has been shown to sustain user engagement (Rudinska & Kolesnikov, 2025).

A critical concern is user trust calibration. Overtrust leads to uncritical acceptance of AI recommendations, while undertrust results in disuse. In AR, recommendations appear as integral parts of the perceived environment, blurring the boundary between AI-generated and human-perceived reality. Explainable AI techniques — saliency maps, confidence indicators, and natural-language justifications — offer solutions by enabling users to assess reliability. Research on immersive decision-making has demonstrated that user trust and engagement are modulated by the quality of environmental feedback and the perceived coherence of the interactive system (Kolesnikov, 2026).

Limitations include the aggregation of data from heterogeneous studies with varying methodologies and AR hardware. Future research should conduct controlled longitudinal studies within standardized AR platforms, investigate LLM-based conversational decision support, and develop standardized evaluation frameworks for AI-augmented AR systems.

6. Conclusions

This paper presented a five-layer conceptual framework for AI-augmented AR decision support integrating perception, reasoning, knowledge, adaptive feedback, and multimodal interaction. Comparative analysis demonstrated that ML-based AI achieves 79–86% accuracy versus 47–58% without AI support, with 34% faster decisions and 35% less cognitive load. These findings establish AI as an essential enabler for effective decision-making in AR environments, transforming AR from a passive visualization medium into an active cognitive partner. Critical challenges remain in trust calibration, explainability, and ethical governance.

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DEEP LEARNING ARCHITECTURES FOR GESTURE RECOGNITION

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The growing demand for natural and intuitive human-computer interaction (HCI) has stimulated substantial research interest in automated gesture recognition systems capable of interpreting human body movements from video sequences. Applications ranging from virtual and augmented reality (VR/AR) interfaces to contactless control systems, security monitoring, and medical rehabilitation increasingly rely on the ability to accurately classify complex spatio-temporal motion patterns without manual feature engineering. Deep learning has emerged as the dominant paradigm for this task, offering architectures that automatically learn hierarchical spatial and temporal representations from raw video data. However, the diversity of available deep learning architectures – including 3D Convolutional Neural Networks (3D CNN), hybrid CNN+LSTM models, and Transformer-based approaches – presents a non-trivial selection problem, as each architecture class exhibits distinct trade-offs between classification accuracy, computational cost, inference latency, and scalability. This paper presents a comparative analysis of these three architecture families for gesture recognition for intelligent human motion identification using the Jester video dataset [1].

Three-Dimensional Convolutional Neural Networks (3D CNN) represent a foundational approach to spatio-temporal video analysis. Unlike conventional 2D CNNs that process individual frames independently, 3D CNNs employ convolutional kernels of size (t × h × w) – where t denotes the temporal dimension – thereby