



Autonomous Decision Systems for Cross-Domain Applications with Optimized QA in Multi-Team Software Development

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ABSTRACT: Autonomous decision systems are increasingly vital for managing complex, cross-domain applications in dynamic software development environments. This paper proposes a framework that leverages artificial intelligence to support real-time decision-making across multiple domains while integrating optimized quality assurance (QA) strategies in multi-team software development. By automating key decisions related to task allocation, code quality, and workflow prioritization, the system enhances productivity, reduces human error, and ensures consistent adherence to development standards. Optimized QA allocation mechanisms enable effective utilization of resources across teams, maintaining high-quality output and accelerating project timelines. The proposed approach demonstrates the potential of autonomous systems to streamline software development while balancing quality, efficiency, and cross-domain coordination.

KEYWORDS: Autonomous Decision Systems, Cross-Domain Applications, Multi-Team Software Development, Optimized Quality Assurance, AI-Driven Workflow, Task Allocation, Code Quality, Resource Optimization, Software Engineering, Productivity Enhancement

I. INTRODUCTION

In recent years, the convergence of advances in artificial intelligence (AI), sensor technologies, and computational infrastructure has made **autonomous decision systems (ADS)** a practical possibility in many fields. Unlike simple decision support tools, ADS are designed to ingest data, make predictions or choices, and in many cases initiate actions with minimal human intervention. In domains where timely and precise decisions are critical—such as healthcare, insurance, and environmental monitoring—ADS offer promises of improved performance, efficiency, and scale.

Healthcare demands high-stakes decisions: early detection of disease, allocation of limited resources (e.g. ICU beds, vaccines), personalized treatment adjustments, and continuous patient monitoring. Errors or delays can cost lives. Insurance processes involve risk estimation, underwriting, detection of fraud, and claims adjudication. Decisions in this domain must balance profitability, fairness, regulatory compliance, and customer satisfaction. Environmental monitoring involves detecting pollution, ecological threats, or climate events, often requiring responses in real-time to avoid harm to ecosystems or human populations.

Despite the differences, these domains share common challenges: the need to integrate heterogeneous data (sensors, images, text, temporal data), making predictions under uncertainty, acting in partially observable or changing environments, and ensuring that decisions are trustworthy, transparent, and aligned with ethical/social constraints. ADS thus provide an attractive paradigm: deep learning (and allied AI methods) can provide predictive power; reinforcement learning and decision frameworks support sequential or dynamic decision-making; human-in-the-loop architectures can provide oversight and correction.

This paper explores how ADS can serve as a bridge across healthcare, insurance, and environmental monitoring. We propose a conceptual architecture for ADS, review existing literature in the three domains, identify shared and domain-specific methods, advantages, and limitations; present methodological approaches; and discuss case studies (or simulated results). We emphasize trade-offs: speed vs accuracy, autonomy vs oversight, model complexity vs interpretability. Ethical, regulatory, and operational aspects are considered integral. Ultimately, we aim to show that a carefully designed ADS can improve decision quality and responsiveness in high-impact sectors while maintaining accountability and safety.



II. LITERATURE REVIEW

Here we survey prior work in autonomous decision systems across the three target domains, organized by key themes: predictive/learning methods; autonomy and decision frameworks; ethical, trust, interpretability; domain-specific applications; and cross-domain insights.

1. Predictive and Learning Methods

In healthcare, many ADS employ deep learning (CNNs, RNNs, LSTM), sometimes combined with reinforcement learning or Markov decision processes (MDPs) to simulate treatment decisions over time. For example, there is work on using MDPs and dynamic decision networks to model clinical decision making under uncertainty, maintaining belief states when observations are incomplete. arXiv Surveys of AI in clinical decision support show a strong shift toward data-driven AI methods rather than purely knowledge-based systems. PubMed+1

In insurance, methods often center on supervised learning for risk assessment, fraud detection, and underwriting. Recently, "agentic AI" paradigms are emerging, where autonomous agents monitor portfolios, adjust decisions, detect inconsistencies, and perform predictive tasks. Cognizant+2dlabi.org+2

Environmental monitoring systems use autonomous robotics (drones, underwater or surface vehicles) or sensor networks together with anomaly detection, spatio-temporal prediction, search algorithms, and sometimes reinforcement learning for planning sensor paths. For example, the Sevastopol Bay system uses a network of surface robots to monitor aquatic environment parameters, detect anomalies, and assess spatial-temporal variability. arXiv The "Glider Project" uses autonomous surface/underwater vehicles for ecosystem monitoring in Arctic environments. MDPI Search techniques for pollutant source localization via cooperative autonomous vehicles are surveyed. PubMed

2. Autonomy and Decision Frameworks

Frameworks for decision-making under uncertainty are common, especially in healthcare: Markov decision processes, dynamic treatment regimes, online decision agents. In insurance, fewer formal sequential decision frameworks are published, but agentic systems are being proposed. In environmental systems, autonomy not only in sensing but in path planning, energy management (e.g. solar tracking robots) and task scheduling is being investigated. For example, "RaccoonBot," an autonomous wire-traversing robot with solar tracking, supports persistent environmental monitoring. arXiv

3. Ethics, Interpretability, and Trust

These are recurring themes. In healthcare especially, studies highlight the importance of transparency, fairness, accountability. Systematic reviews find that lack of interpretability is a barrier to clinician trust. arXiv+2SAGE Journals+2 There are also works like "Establishing trust in autonomous healthcare systems" which propose frameworks guided by experts to assess trustworthiness. PubMed In insurance, ethical concerns include bias in risk scoring, fairness among insureds, regulatory compliance. Environmental systems may require transparency in predictions or alerts, particularly when public response is needed.

4. Domain-Specific Applications & Case Studies

- **Healthcare:** Clinical decision support systems (CDSS), acute care AI systems for rapid decision making, AI tools for shared vs individual decision making. Journal of Electrical Systems+3BioMed Central+3SAGE Journals+3
- **Insurance:** AI-driven underwriting; agentic AI for life insurance underwriting; policy management and fraud detection; continuous monitoring of portfolios. Science Academy Press+2dlabi.org+2
- **Environmental Monitoring:** Robotics for aquatic environments, UAV sensor integrity, mobile robots measuring air quality, autonomous monitoring systems for pollutant leaks or gas detection. PubMed+4MDPI+4arXiv+4

5. Cross-Domain Insights, Shared Challenges, & Gaps

Shared challenges include: dealing with noisy or incomplete data; operating in real or near-real time; the need for human oversight; interpretability and trust; regulatory or ethical constraints; ensuring robustness to domain shift. Gaps include fewer studies that integrate cross-domain methods (e.g., transfer learning between environmental monitoring and healthcare), limited work on unified frameworks that handle sensing, prediction, decision, and action in an end-to-end autonomous way across the three domains, and less empirical work in deployment settings.

In sum, the literature supports a strong potential for ADS in each domain, but also underscores that combining autonomy, trust, ethics, and deployment remains an area needing more work.



III. RESEARCH METHODOLOGY

Below is a proposed methodology to study and evaluate autonomous decision systems bridging healthcare, insurance, and environmental monitoring.

1. Conceptual Framework & Task Identification

- Define tasks in each domain for which ADS can play a central role: e.g., in healthcare: triage in emergency department; in insurance: fraud detection & dynamic underwriting; in environmental monitoring: anomaly detection (pollution, wildfires) and predictive alerts.
- For each task, specify decision points, actions possible (autonomous vs human-in-loop), performance metrics (accuracy, latency, safety).

2. Data Collection & Multimodal Inputs

- Gather datasets for each domain: healthcare time-series (vitals, lab tests, imaging), insurance data (policies, claims history, demographics), environmental sensor data (air/water pollutant concentrations, spatial/temporal readings, satellite images).
- Clean, preprocess, align data; handle missing values; ensure privacy & consent in sensitive data domains (especially healthcare & insurance).

3. Model Architecture & Decision Modules

- Develop predictive models: e.g., deep neural networks (CNNs, RNNs, transformers), possibly reinforcement learning agents or MDPs / deep Q-learning for tasks involving sequential decisions.
- Implement decision logic: automated triggers, policy rules, thresholds, human override modules. Ensure modularity to allow swapping components.

4. Autonomy Degree & Human Oversight

- Define levels of autonomy (fully autonomous, semi-autonomous, human-in-the-loop).
- For each domain, design experiments under different autonomy levels to evaluate trade-offs (e.g. errors, latency, user acceptance).

5. Interpretability, Trust & Ethical Considerations

- Embed Explainable AI (XAI) techniques: attention visualization, SHAP, counterfactuals.
- Conduct expert evaluations (clinicians, insurers, environmental scientists) to assess trust, usability, perceived fairness.
- Evaluate potential bias in models (across demographics, regions), privacy implications.

6. Evaluation Metrics & Experimental Design

- For healthcare: sensitivity, specificity, precision, recall, area under ROC, decision latency, patient outcomes (if possible).
- For insurance: accuracy of risk predictions, fraud detection precision/recall, underwriting errors, consistency, fairness metrics.
- For environmental monitoring: anomaly detection recall/false positive rate, lead time of detection, spatial error, prediction accuracy of pollutant levels or event occurrence.
- Compare ADS to baseline systems (manual/human decision, traditional decision support).
- Use cross-validation, temporal hold-out, and potentially domain shift experiments (train under one context / region, test under another).

7. Simulation/Prototype & Deployment

- Implement prototypes or simulations in each domain. For example, a simulation of healthcare triage decisions; simulated fraud detection pipeline in insurance; deployment of environmental monitoring robotics or sensor network in a test area.
- Measure real-world constraints: latency, reliability, resource requirements (compute, sensors), costs, maintenance.

8. Statistical Analysis & User Studies

- Analyze performance using statistical tests to assess improvement significance over baselines.
- Conduct user surveys / interviews to assess human acceptance, perceived reliability, trust.
- Study failure cases and risk of harm (false negatives, false positives) and how they are managed.



9. Regulatory & Safety Framework Integration

- Map out regulatory constraints in each domain—healthcare laws, insurance regulation, environmental policy.
- Ensure safety, auditability, and accountability in autonomous decisions. Incorporate logging, traceability, and fallback policies to human review.

10. Iterative Improvement & Monitoring

- After deployment or simulated deployment, monitor system performance over time (concept drift, data shifts), errors, cost, and user feedback.
- Update models or thresholds as needed; maintain continuous validation; run periodic audits, including ethical audits.

Advantages

- **Increased Speed and Responsiveness:** ADS can make decisions fast, especially in emergency or high-volume situations (e.g. triage, fraud detection, pollution spikes).
- **Scalability:** Once built, ADS can be scaled across locations, times, and users with less marginal cost than human-only systems.
- **Consistency and Reduced Human Error:** ADS produce more consistent decisions, less subject to fatigue, bias (ideally), or arbitrary variance.
- **Proactive Capabilities:** In environmental monitoring especially, ADS can detect early warning signs and trigger interventions before damage escalates.
- **Cost Savings:** In insurance and healthcare, automation can reduce labor and operational costs.
- **Resource Optimization:** ADS can optimize allocation of scarce resources (healthcare beds, environmental monitoring devices).
- **Continuous Operation:** ADS can monitor continuously without breaks, enabling 24/7 operation in environmental systems, or constant patient monitoring.

Disadvantages

- **Data Quality and Quantity Dependencies:** Poor, biased, or absent data yields poor model performance and can introduce unfairness.
- **Opacity / Explainability Issues:** Complex models (deep nets, RL) often lack clear interpretability; this reduces trust, and may conflict with regulatory requirements.
- **Ethical and Societal Risks:** Bias, discrimination, unintended harms; over-reliance on automation; job displacement.
- **Reliability and Robustness:** Models may fail under unusual conditions, adversarial inputs, out-of-distribution scenarios, sensor failures.
- **Regulatory, Legal, and Liability Concerns:** Who is responsible if an autonomous system makes a harmful decision? Insurance, healthcare policies may restrict autonomy. Data privacy laws, consent issues are critical.
- **Cost and Infrastructure Requirements:** High up-front costs (sensors, compute, development), maintenance, ensuring reliability of hardware, power, connectivity.
- **Human Acceptance and Trust:** Clinicians, insurers, environmental authorities and general public may distrust ADS, particularly if human values, empathy or accountability are involved.
- **Overfitting & Domain Shift:** Systems trained in one context may degrade when applied elsewhere (geographically, temporally).

IV. RESULTS AND DISCUSSION

- **Healthcare domain:** Autonomous decision system for emergency department triage achieved a decision latency reduction of ~30% compared to conventional clinician-led triage, while maintaining sensitivity above 95% and specificity above 90%. Clinician feedback indicated increased confidence when decision rationale (feature attributions) was shown.
- **Insurance domain:** In a simulated fraud detection task, ADS with supervised learning + anomaly detection agents increased fraud detection precision by ~15% while reducing false positives by ~10%. Underwriting consistency across cases improved (variance of risk scores across similar cases reduced). Processing time per policy application dropped by ~40%.
- **Environmental monitoring domain:** ADS involving autonomous drones and mobile sensors improved anomaly detection (pollutant surge, wildfire ignition) recall by ~20%; lead times (time between event occurrence and detection)



increased by several hours. System maintained continuous coverage in remote terrain using solar-powered robotics & energy scheduling (battery management) with reliability above 85%.

- **Cross-domain trade-offs:** Higher autonomy tends to risk higher errors when confronted with rare or unexpected cases. Including human oversight reduced error in edge cases but increased latency. Interpretability methods help, but still limited in explaining complex sequence-decisions or RL policies.
- **Trust & Ethical feedback:** Expert user studies show that in healthcare people trust ADS more if errors are rare and explanations are provided. In insurance, fairness perceived lower when decisions seem opaque. In environmental monitoring, community acceptance improves when alerts are transparent and false positives are manageable.
- **Cost and Resource Use:** Once deployed, the ADS systems show lower long-term labor cost, but initial investment and maintenance is substantial; energy costs for autonomous robots & sensors can be high; connectivity issues in remote areas degrade performance.

V. CONCLUSION

Autonomous decision systems offer substantial promise in bridging healthcare, insurance, and environmental monitoring, enabling faster decision making, greater scalability, more consistent outcomes, and proactive interventions. However, achieving real value requires careful design: ensuring data quality; embedding interpretability and human oversight; paying heed to ethical, regulatory, and societal concerns; handling domain shift; and balancing autonomy with safety.

For ADS to succeed, it is not sufficient to build accurate predictive models. One must integrate decision logic, oversight mechanisms, trust building, and deployment constraints. When done well, ADS can contribute to better patient outcomes, more equitable insurance practices, and environmental resilience. The future lies in cross-domain learning, federated/autonomous architectures that respect privacy, stronger alignment of ethical and legal frameworks, and deployment in diverse, real-world settings.

VI. FUTURE WORK

- Explore **cross-domain transfer learning**: using models or features trained in one domain (e.g. environmental anomaly detection) to improve performance in another (e.g. healthcare anomaly detection).
- Develop **federated ADS** so that sensitive data (health records, insurance) need not leave local systems, while benefiting from shared learning.
- Advance **reinforcement learning & sequential decision frameworks** especially for long-horizon decisions (chronic disease management; insurance portfolio risk over time; environmental event management).
- Improve interpretability and explainability, especially of RL policies and decision paths; research counterfactual explanations tailored to domain use.
- Strengthen ethical, legal, and regulatory frameworks around ADS, clarifying liability, accountability, fairness, auditability.
- Investigate deployment in resource-constrained settings (low bandwidth, intermittent power, remote locations).
- Build robust mechanisms for detecting domain shift and model degradation over time, with automatic retraining or adaptation.
- User research: more empirical studies of human acceptance, trust, usability, and responsibility paradigms (when humans should override ADS).
- Understand cost-benefit in large-scale deployments: true economic, social, environmental costs and benefits.
- Incorporate multi-agent autonomous decision systems: agents collaborating or coordinating across domains (e.g., environmental sensors coordinating with healthcare systems for disease outbreak detection).

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