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Proceedings

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Plenary Lectures

Quality Engineering

Reliability Engineering

Industrial Engineering

Systems Engineering

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Lean Production

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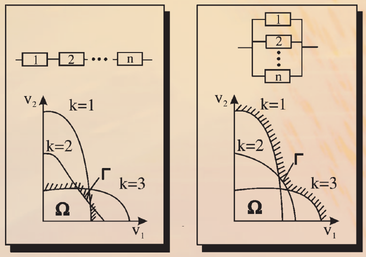

Education

Application

National award for business excellence of Serbia - "Quality Oscar" in 2012. year, in category small and medium organizations, for range Leadership obtained DQM Research Center, Prijevor.

Editor
Ljubisa Papic

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17^{th} DQM International Conference

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PROCEEDINGS

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Conference Topics:

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AI-ENABLED DECISION ARCHITECTURES: A LAYERED MODEL FOR RELIABILITY AND GOVERNANCE

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Summary: *The paper examines AI-enabled decision architectures as complex socio-technical systems operating in dynamic and uncertain environments. It shows that system performance cannot be reduced to algorithmic accuracy, but depends on the interaction between technical processes, human oversight, organizational structures, and governance mechanisms. A layered model of AI-enabled decision architectures is proposed, integrating these interdependent components into a unified analytical framework. The paper identifies key challenges affecting system reliability, including temporal desynchronization between system layers, feedback coupling between model outputs and decision environments, and the problem of trust calibration in human–AI interaction. It is argued that misalignment across these layers represents a primary source of system instability, particularly in large-scale and high-risk environments. Since real-world evaluation of such systems is constrained by operational limitations, it is proposed in this paper an integrated approach to system assessment, combining performance analysis, cross-layer indicators, and lifecycle-based evaluation. The proposed model contributes to the development of methods for improving reliability, risk management, and governance of AI-enabled decision systems.*

Key words: *AI-enabled decision systems, socio-technical systems, system reliability, governance, risk assessment, evaluation.*

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1. INTRODUCTION

Artificial intelligence is increasingly embedded in decision-making processes across complex socio-technical systems, including organizational, military, and digital infrastructures. In such environments, decision outcomes do not arise solely from computational models, but from the interaction between algorithms, human actors, and institutional structures. This integration transforms artificial intelligence from an analytical tool into a structural component of decision architectures that shape how information is processed and applied. Contemporary AI systems achieve high predictive performance under conditions of uncertainty. However, predictive accuracy alone does not ensure reliable system behavior. In real-world settings, decision-making is influenced by organizational routines, human judgment, and governance constraints that extend beyond algorithmic design, which may lead to discrepancies between system optimization and broader institutional objectives and create conditions for systemic risk.

These challenges are particularly evident in systems characterized by high interdependence and dynamic environments. AI systems continuously interact with evolving data, human decision-makers, and organizational processes, generating feedback loops that reshape both the system and its environment. Consequently, system behavior reflects cross-layer dynamics rather than purely technical performance. Despite extensive research on machine learning, human–automation interaction, and AI governance, these dimensions are often examined separately, which limits understanding of how AI-enabled decision systems function in integrated environments and obscures the systemic nature of risk and reliability. To address this gap, it is proposed in this paper a layered model of AI-enabled decision architectures that integrates technical processes, human interaction, organizational embedding, and governance structures within a unified framework. The central argument is that system stability depends not only on algorithmic accuracy, but on the alignment and synchronization of these interconnected layers. From an engineering perspective, this approach shifts the focus from isolated model evaluation toward system-level reliability and provides a basis for analyzing risk, improving coordination, and supporting lifecycle-based system management.

2. LAYERED MODEL OF AI-ENABLED DECISION ARCHITECTURES

The proposed model conceptualizes AI-enabled decision systems as integrated structures in which several interdependent dimensions operate simultaneously. Rather than treating artificial intelligence as a self-contained technical component, the model emphasizes that decision outcomes emerge from the interaction of computational processes, human judgment, organizational routines, and governance frameworks. At the technical level, decision-making relies on machine learning models and adaptive optimization processes, often grounded in reinforcement learning and iterative feedback loops. Although these systems can achieve high performance, their behavior depends on predefined objective functions that rarely capture the full complexity of real-world goals. As a result, even well-performing models may generate unintended outcomes when reward structures are incomplete or imperfectly specified [2]. This underscores that optimization is conditioned by how objectives are defined, rather than being inherently aligned with broader institutional priorities.

At the same time, AI systems remain embedded in environments where human actors play a decisive role. Operators and decision-makers interpret outputs, determine levels of reliance, and decide when intervention is required, meaning that system performance depends not only on algorithmic quality but also on how users engage with the system. Beyond individual interaction, these systems are situated within organizational contexts that shape how information is processed and decisions are made, creating feedback loops in which system outputs influence behavior, while that behavior affects future data. These processes are further embedded in governance frameworks that define accountability, allocate responsibility, and establish oversight mechanisms, which are essential for ensuring transparency and managing risk [6,7]. Taken together, these dynamics indicate that AI-enabled decision architectures are not purely technical systems, but multi-layered configurations in which performance and reliability depend on the continuous alignment of interconnected components.

3. CROSS-LAYER RISKS AND SYSTEM MISALIGNMENT

System instability in AI-enabled decision architectures rarely originates within a single component, but more often emerges at the interfaces where different layers interact. Technical, human, organizational, and governance layers operate according to distinct logics and temporal dynamics, and when these are not aligned, even well-designed systems may produce outcomes that are difficult to anticipate or control. A key source of instability lies in differences in adaptation speed: AI systems update continuously, often in near real time, while organizational processes evolve more gradually and governance frameworks change even more slowly, typically in response to significant events. These temporal mismatches create synchronization gaps in which decisions may rely on already outdated models, while institutional responses lag behind. Over time, such desynchronization can undermine both reliability and accountability, not because individual components fail, but because they no longer function in a coordinated manner.

Additional risks arise from recursive feedback between system outputs and the environments in which they are applied. AI systems shape the data they subsequently rely on, as decisions informed by algorithmic outputs influence user behavior, organizational priorities, and information flows. This feedback dynamic can reinforce existing patterns, stabilize biases, and reduce the system’s capacity to adapt to new conditions [8]. At the same time, effective use of AI depends on maintaining a balance between trust and skepticism. Excessive reliance on automated outputs may lead to uncritical acceptance, while insufficient trust can result in underutilization, both of which degrade system performance [3,4]. These challenges are further amplified by scale, as even minor errors may propagate rapidly across interconnected processes, creating systemic vulnerabilities that require timely detection and coordinated response [9]. Taken together, these dynamics indicate that risk in AI-enabled decision architectures arises less from isolated technical failures and more from insufficient alignment across interacting system layers.

4. ENGINEERING RELIABILITY IN AI-ENABLED SYSTEMS: A CROSS-LAYER PERSPECTIVE

The layered perspective developed in this paper has direct implications for how AI-enabled systems are designed, evaluated, and managed in engineering contexts. Rather than treating artificial intelligence as a standalone technical solution, reliability should be understood as an emergent property of the entire system. In practice, this means that system performance cannot be assessed solely through metrics such as accuracy or convergence, since even highly accurate models may contribute to instability if they are not aligned with organizational objectives, if human oversight is insufficient, or if governance mechanisms fail to ensure effective control. This is consistent with findings that optimization processes, particularly in reinforcement learning systems, depend critically on how objectives are specified and may produce unintended outcomes when these are incomplete or imperfectly defined [2]. Reliability therefore depends on maintaining coherence across interdependent processes, including alignment of objectives, effective human–AI interaction shaped by trust dynamics [3,4], organizational capacity for adaptation and learning [5], and governance mechanisms that ensure transparency, accountability, and risk control [6,7].

From an engineering perspective, this coordination can be assessed through indicators that capture interactions between system layers rather than relying only on technical performance metrics. Measures such as synchronization latency, oversight response time, and the balance between model updates and organizational adjustments provide insight into how systems function under real operational conditions [1]. At the same time, risk management must be approached in an integrated manner, as risks emerge from the interaction of technical, organizational, and governance factors. Technical risks relate to model robustness and sensitivity to changing data, organizational risks to system integration and feedback dynamics [8], and governance risks to broader system impacts, particularly in large-scale deployments [9]. Finally, adopting a lifecycle perspective is essential, as key challenges arise at different stages of system development—from objective specification and deployment to monitoring and recalibration. Continuous evaluation and adaptation, as emphasized in resilience research, are therefore necessary conditions for maintaining system functionality under changing and uncertain conditions [10].

5. CONCLUSION

AI-enabled decision architectures should be understood as complex socio-technical systems rather than isolated computational models. Their performance is shaped not only by algorithmic design, but by the interaction of technical processes, human judgment, organizational structures, and governance mechanisms. The layered perspective developed in this paper highlights that system stability depends on coordination across components that operate according to different logics and timescales. While technical systems evolve rapidly, organizational and governance processes adapt more gradually, creating conditions in which misalignment may emerge even when individual components function effectively. Such cross-layer misalignment represents a key source of systemic risk in AI-enabled decision environments.

This perspective implies that reliability should be treated as a continuous process rather than a fixed property, requiring ongoing monitoring, adjustment, and recalibration, particularly in dynamic and uncertain contexts. As AI systems scale and become more deeply embedded in organizational and institutional settings, their influence extends beyond efficiency gains and increasingly shapes decision structures and outcomes. For this reason, effective system design must integrate technical performance with organizational and governance considerations from the outset. Future research should focus on the empirical validation of cross-layer indicators and the development of integrated evaluation frameworks capable of capturing system behavior in real-world conditions, thereby supporting the design of AI-enabled systems that are not only effective, but also robust and sustainable over time.

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