

Integrating Neurosymbolic AI in Advanced Air Mobility: A Comprehensive Survey

Kamal Acharya¹, Iman Sharifi², Mehul Lad¹, Liang Sun³, Houbing Song¹

¹UNIVERSITY OF MARYLAND BALTIMORE COUNTY, ²THE GEORGE WASHINGTON UNIVERSITY, ³BAYLOR UNIVERSITY



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- AI has shifted from symbolic logic to opaque neural nets, both insufficient alone
- Neurosymbolic AI integrates learning and reasoning to overcome this divide
- AAM promises air transit integration via eVTOLs and automation
- Current AAM challenges: regulatory gaps, safety concerns, and fragmented data
- AAM success demands AI that is both adaptive and explainable

- Neurosymbolic AI offers interpretable, constraint-aware decision-making
- Learns from real-time data; reasons with domain rules (e.g., airspace, safety)
- Enables dynamic path planning, traffic coordination, and compliance
- This survey bridges Neurosymbolic AI and aviation domains

- Hybrid AI merging neural learning with symbolic reasoning
- Symbolic AI: explainable, structured, but rule-heavy
- Neural AI: data-driven but opaque and less interpretable
- Neurosymbolic AI: efficient, explainable, and requires less data

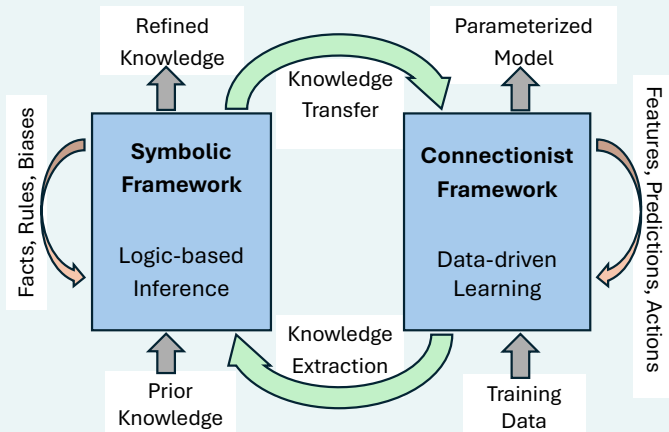


Figure: General interactions between symbolic and connectionist frameworks in Neurosymbolic AI

- Paradigm shift in transportation via eVTOL, UAM, and RAM.
- Driven by electric propulsion, automation, and autonomy.
- Challenges: battery tech, UTM systems, public acceptance.

Technological Advancements Driving AAM

eVTOL Aircraft

Autonomous Flight
and
Traffic Management

Cellular Connectivity
and
Communication Networks



Applications and Use Cases

Urban Air Mobility

Cargo Delivery
and
Logistics

Emergency Medical
Services

Figure: AAM Overview

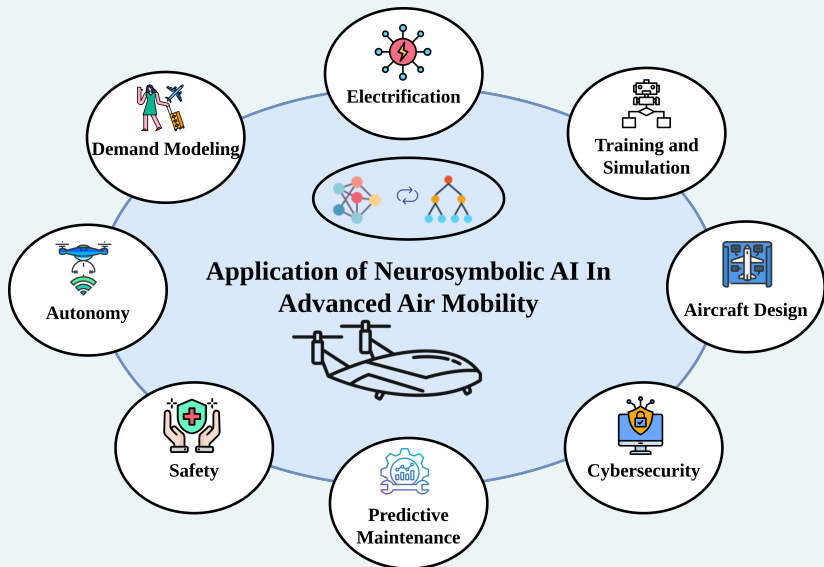


Figure: Applications of Neurosymbolic AI in AAM

- Phased, risk-based AI integration in aviation.
- Start with low-criticality systems → gather operational data → scale to safety-critical.
- Iterative approach links early insights to later deployments.
- Defines:
 - Learned AI: static, pre-trained.
 - Learning AI: adaptive, unpredictable.
- Certification challenges: unpredictability, bias, limited explainability.

- Foundation for AI in aviation: ML & DL in design, operations, maintenance, ATM, drones, and safety.
- Focus on trustworthiness:
 - Explainability.
 - Human-AI collaboration.
 - Phased certification.
- Safety-driven, reliability-first integration approach.

- Broader scope: hybrid AI (incl. Neurosymbolic), digital twins, predictive maintenance.
- Stronger emphasis: cybersecurity & AI safety assurance.
- Human centric, augmentation-focused vision.
- Risk-based AI categorization aligned with EU AI Act.
- Mandates transparency, explainability, and human oversight.

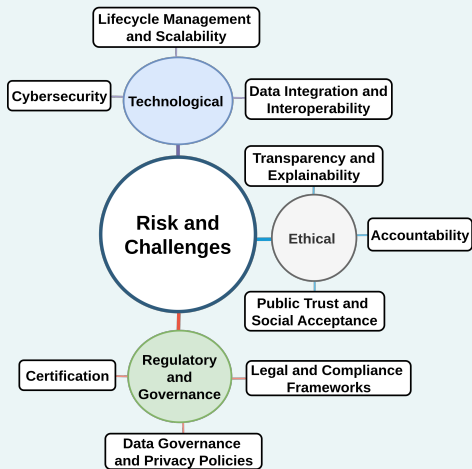


Figure: Risks and Challenges

- Neurosymbolic AI offers interpretability + adaptivity.
- Enables transparent and certifiable AAM systems.
- Future: Standardization, ethical compliance, interdisciplinary research.

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Thank You