Enhancing Evaluation and Testing of AI-Enabled Systems in the DoD using Model Based Systems Engineering

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Agenda

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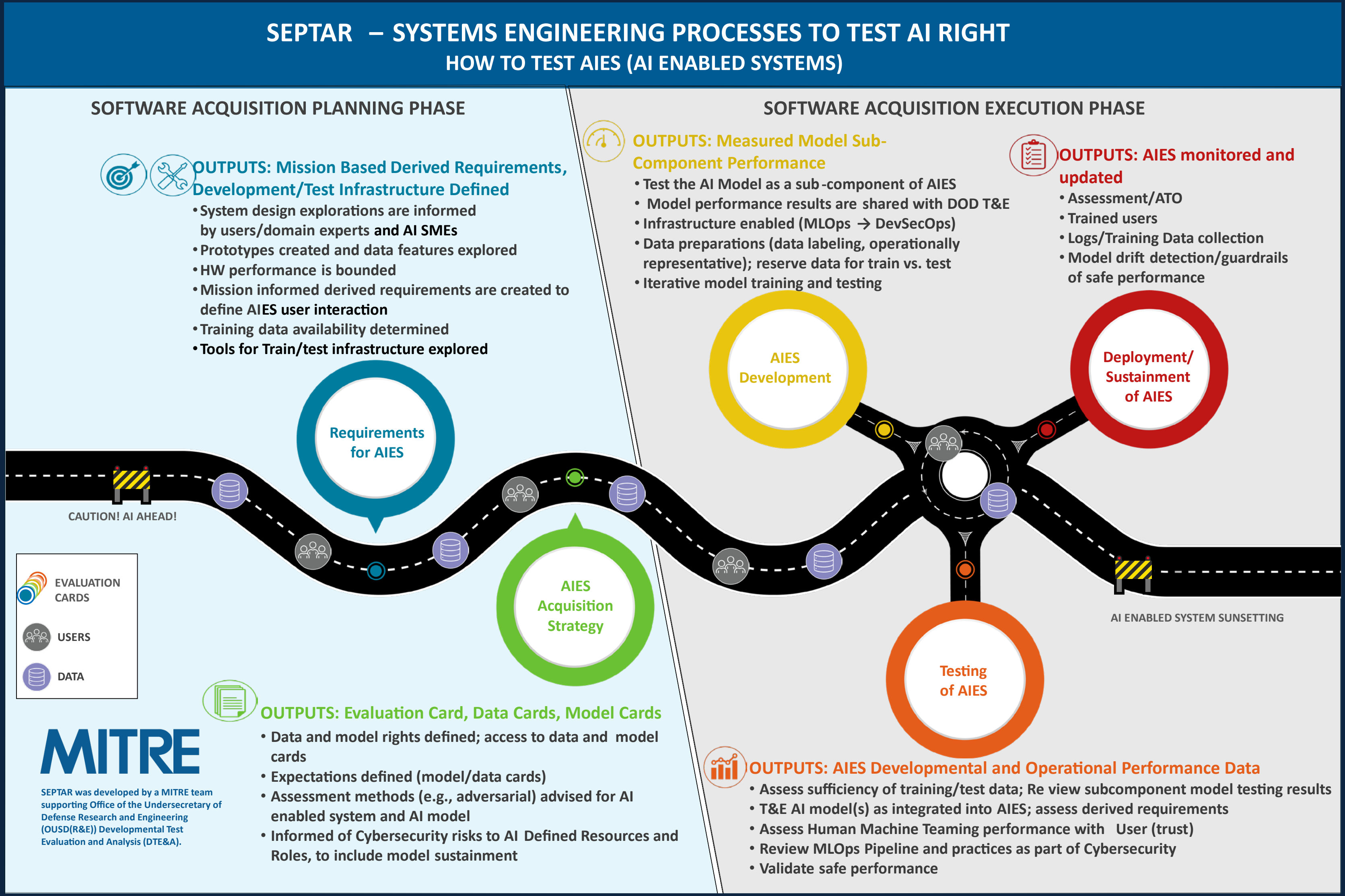
SEPTAR Alignment

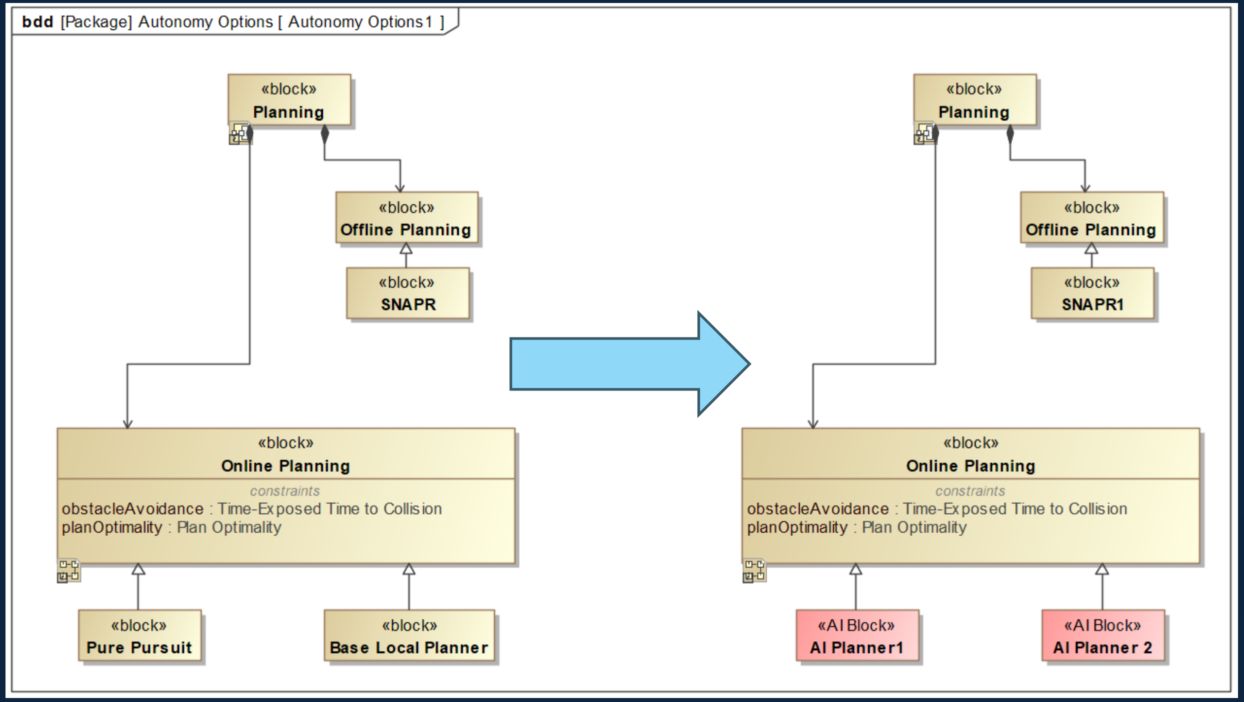
This work addresses a focus area within the Systems Engineering Processes to Test AI Right (SEPTAR) Framework which defines a broader T&E Continuum for AIES

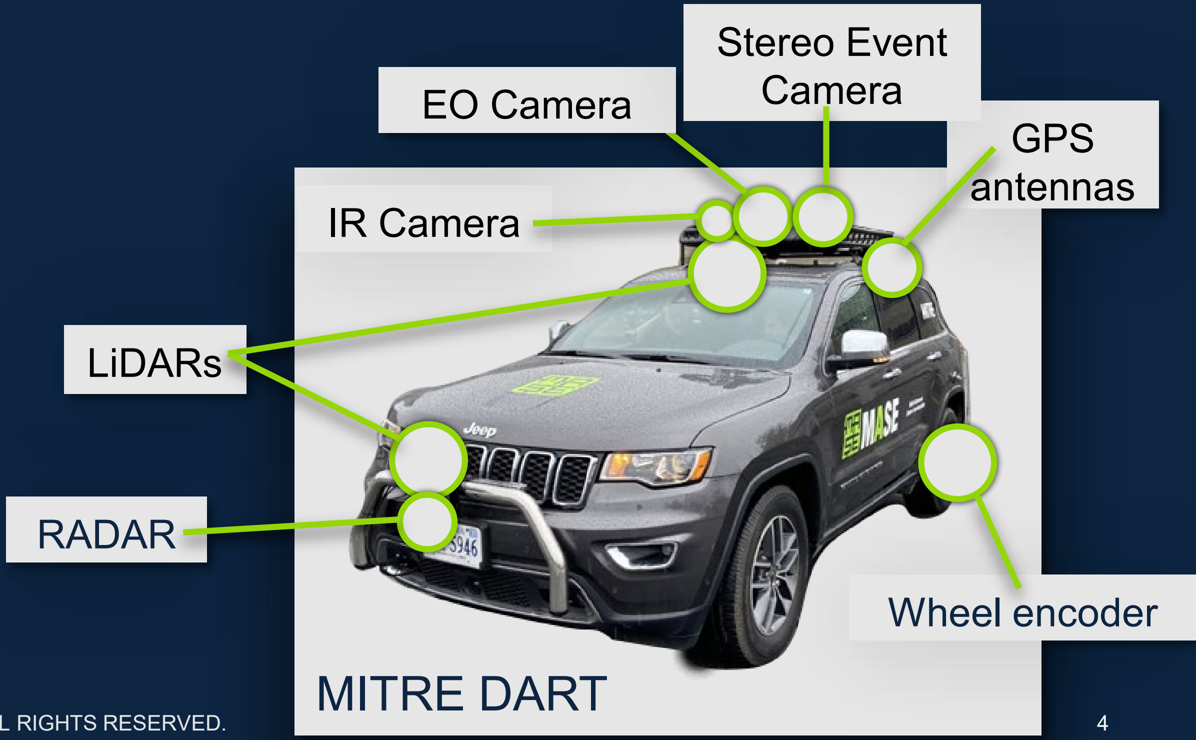


Use Case: Autonomous Ground Vehicle (AGV)

We grounded our work in an MBSE use case of an AI-enabled system (AIES)

- DART-AGV project is a MITRE program in support of Army Research Lab
  - Goal is to evolve an MBSE model for an autonomous vehicle system to include AI components.
- Team modified ARL-provided MBSE model to include an Artificial Intelligence Online Planner
  - Added and modified views to highlight the AI component and its interactions

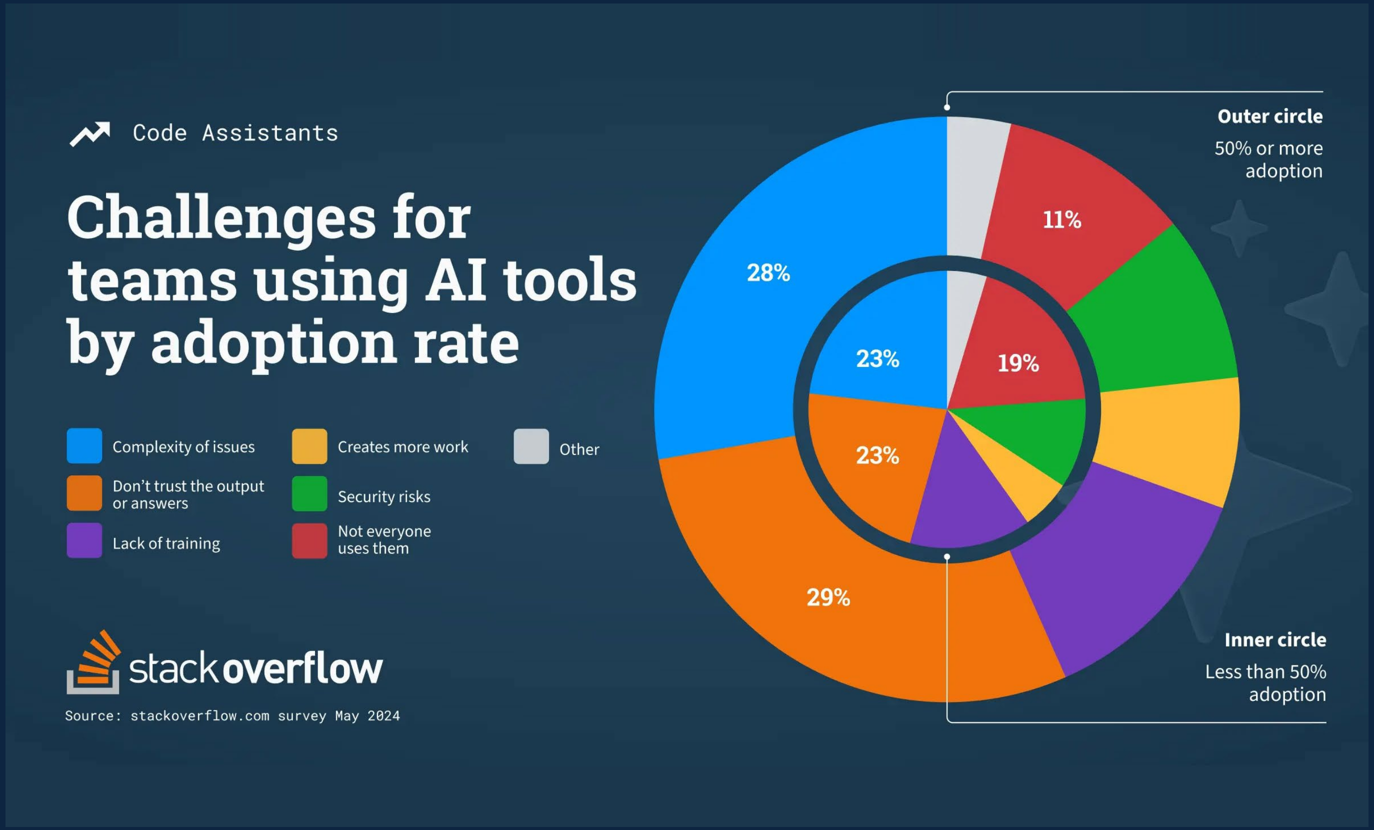




Model-View AI Challenges & Recommendations

T&E of AIES Challenges

1. Functional Behavior of AIES Can Include Learning Components
2. AIES Behavior Continuously Adapts and Evolves Over Time
3. Challenges of Human Review and Accountability for AIES Performance
4. AI Model Training and Bias
5. Cybersecurity of AIES
6. Limited “awareness” (context for decision-making)
7. Leveraging AI Model Transparency



Insights gained via MBSE can help mitigate these T&E challenges

MBSE Mitigations to the T&E of AIES

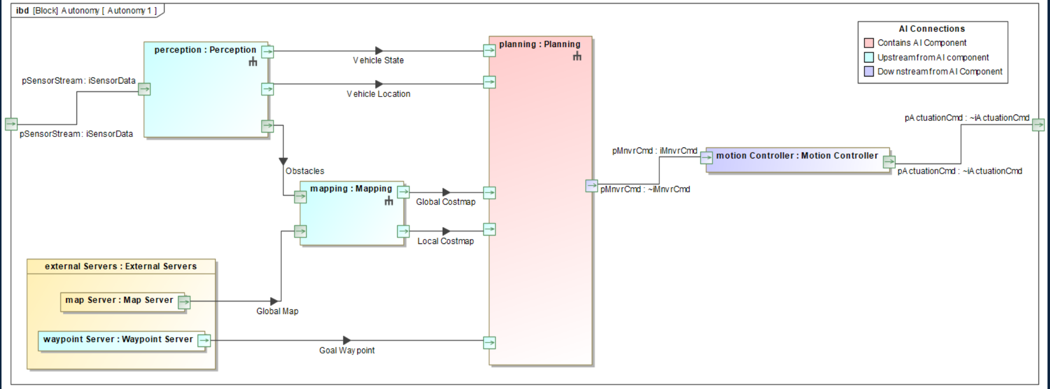
Functional Behavior of AIES Can Include Learning Components

T&E Limitation(s):

- T&E is difficult to conduct without clearly defined inputs and outputs due to the lack of transparency in how AI model parameters lead to decisions and the potential for AI models to continuously learn.
- More directly, it is difficult to build or evaluate good tests without a clear understanding of the parameters that determine the underlying AI model's performance. In a fully "Black Box" scenario, test activities must be conducted around the inputs and outputs of the AI sub-component(s) interacting with the rest of the AIES.

MBSE Mitigation(s):

- Block Diagrams: If the input/output for an AIES is known, AI *sub-component interfaces* can be entered into block definition diagrams (BDDs) or internal block diagrams (IBDs) in SysML.
  - IBDs show relationships between AI and non-AI sub-components to *characterize interfaces for evaluation* to fully assess an AI sub-component. Diagrams such as these can show what data elements are inputs or outputs of an AI component to consider in test design and test case prioritization to fully inform the risks around AI performance.
- Constraint Diagrams: MBSE can also demonstrate *a range of outputs* that are acceptable for the AIES and clearly define the limits of these ranges.
  - Numerical or quantitative *constraints captured* in a constraint diagram that define the AIES performance can potentially be checked through automated T&E or to inform T&E activities that occur through more manual processes.



AI enabled subcomponent (pink box in the center) interacting with several other non-AI enabled sub-components.

Element Type: Constraint Block ... Scope (optional): Autonomy Metrics,Autonomy Parameters,Environr ... Filter:

#	Name	Owner	Constraints	Refines
1	Learning and Adaptability	Planning	Error Rate=Error rate should decrease by X% after ...	145 Learning and Adaptability
2	Training Data Bias and Fairness	Planning	Error Rate for different environmental situations=...	143 Bias and Fairness
3	Robustness and Resilience	Planning	Return to normal behavior=Time < 1 minute	142 Robustness and Resilience
4	Continuous Monitoring and Evaluation	Planning	System performance evaluation every=Time < 1 hour	146 Continuous Monitoring and Evaluation
5	Data Privacy and Security	Planning	Data storage encryption key length =Key Length > X...	147 Data Privacy and Security

Constraints defined for AIES performance.

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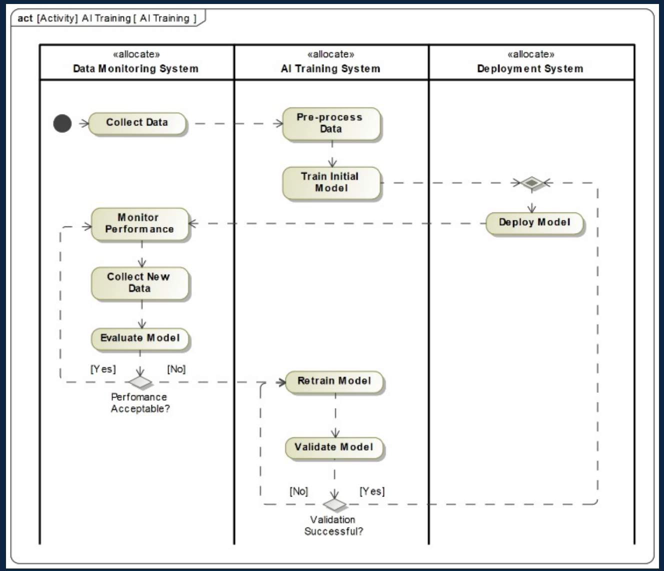
MBSE Mitigations to the T&E of AIES
AIES Behavior Continuously Adapts and Evolves Over Time

T&E Limitation(s):

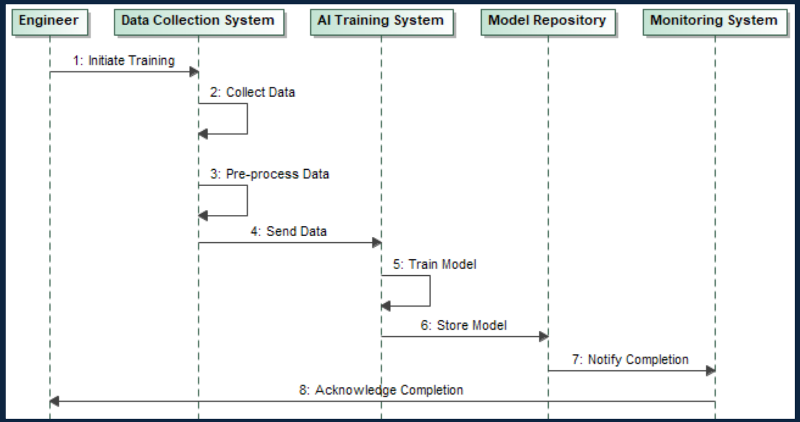
- It may be expensive, infeasible or impractical to re-test the AIES every time the AI models change as a normal part sustainment. The continuous changes and updates of AI models will create challenges for T&E.

MBSE Mitigation(s):

- <u>Activity diagrams</u> – Assessing continuously evolving systems benefits from the <u>*application of automated testing techniques*</u>.
    - Activity diagrams can inform these practices, providing a clear understanding of the mission and use of the AIES (and sub-system) and enables effective automated resources assessment.
    - In cases where AIES systems have self-instrumentation built into collect key test data automatically (e.g., model performance changes), an activity diagram can show clearly where and how the data was collected.
- <u>Sequence Diagrams</u>: Within a sequence diagram it should be clear what lifelines are AI components so messages upstream or downstream from it are well defined.
    - This informs T&E of potential <u>*key dependencies or bottlenecks*</u> for exploration in automated testing to facilitate rapid redeployment.



Activity diagram of AI retraining process.



Sequence diagram of AI training and deployment

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MBSE Mitigations to the T&E of AIES

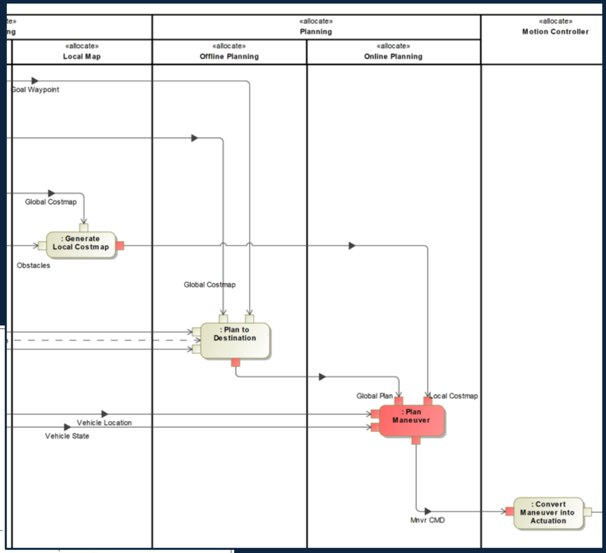
Challenges of Human Review and Accountability for AIES Performance

T&E Limitation(s):

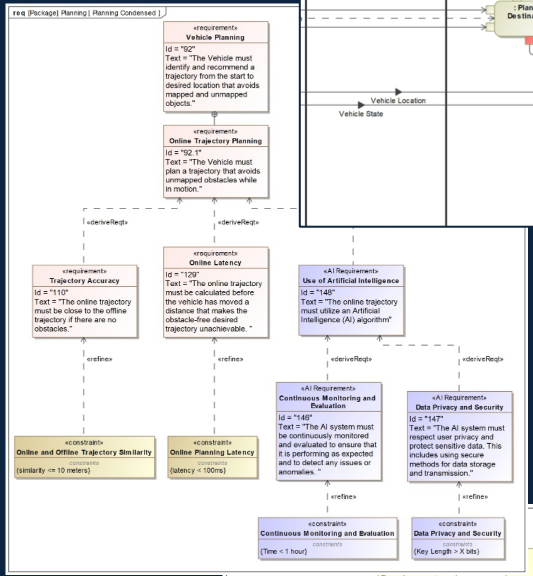
- It is difficult to enable T&E or human evaluators to assess capability performance due to lack of transparency in explainable AI, AIES, and self-reporting confidence scores.

MBSE Mitigation(s):

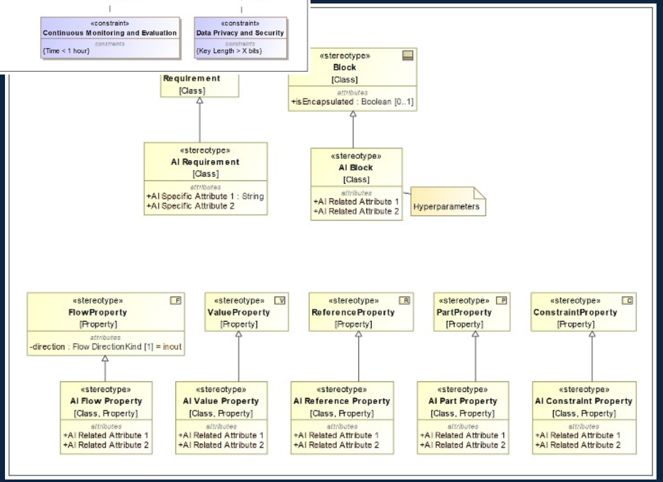
- Activity Diagrams – System-level activity diagrams document behaviors of system or sub-system elements and user behavior as they interact with the element.
  - Activity diagram swim lanes clarify the responsibilities of specific parts of the system. T&E can discern *which elements are performed by the AI components and which human decisions and activities* are upstream and downstream from those AI enabled activities.
- Requirements Diagram – Requirements diagrams visually represent the landscape and relations between requirements and other elements.
  - Derived requirements note the presence of AI (blue box) and capture specifics of AI model technology choices. *The derived AI requirements outline the expected behavior, performance, and constraints* within the AIES as it supports the user and mission.
  - Operational descriptions captured in the figure show key considerations for data privacy to ensure appropriate test planning and data privacy practices for test.
- MBSE Stereotype - A stereotype for AI-related requirements/derived requirements for MBSE to extend the SysML Requirement Class.
  - AI-specific stereotypes capture additional *properties for AI-related derived requirements* and provide clear differentiation *to enable T&E.*



Activity diagram for AI component



AIES-derived requirements diagram



Requirements diagram with stereotyped reqts

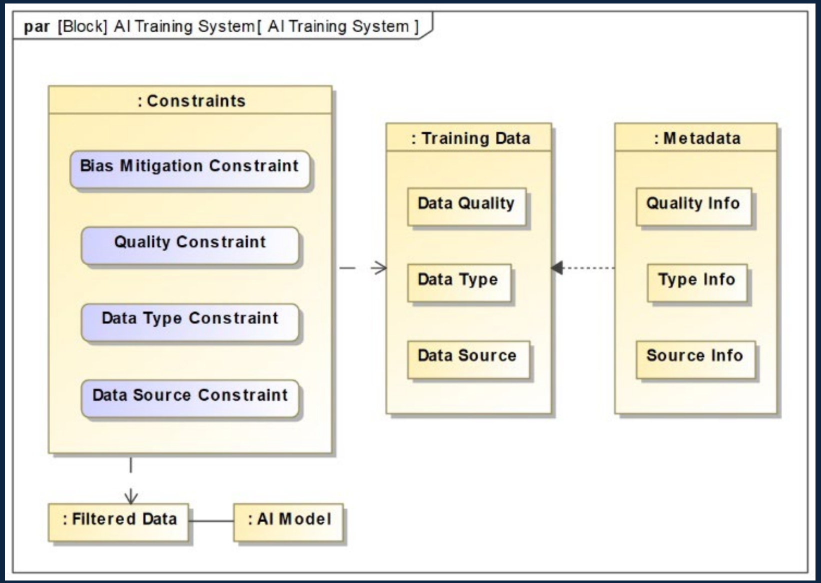
MBSE Mitigations to the T&E of AIES
AI Model Training and Bias

T&E Limitation(s):

- Techniques to ensure data used to train the AIES is of sufficient volume and quality to assess the AIES are still emerging. Testing for bias in data must be grounded with an understanding of the operational environment where the AIES will perform and understood by T&E.

MBSE Mitigation(s):

- Parametric Diagram: MBSE defines the range of conditions that the AIES must perform under once operationally deployed.
    - T&E can *compare expected operational context to the data used to train the AIES* to ensure model training data represents operational conditions and avoids bias. If bias cannot be avoided, T&E must ensure appropriate process mitigations are documented (e.g., tactics, techniques, and procedures).
    - MBSE may help the tester *identify cases of data bias* if proper metadata is available. Models can have constraints and boundary conditions to ensure only a certain amount, certain types, or a filtered set of data is used to train an AI component.
    - With a digital toolchain, AI models could be trained with different weights, constraints, and boundaries to create an AI model that mitigates bias. This will have some human-in-the-loop interactions, but MBSE can automate and organize the process, resulting in a better AI component.



Parametric diagram of constraints and AI components

MBSE Mitigations to the T&E of AIES
Cyber T&E of AIES

T&E Limitation(s):

- Each type of AIES will have its own set of cyber vulnerabilities and attacks against it may be indirect (e.g., targeting related elements like training/test data, user inputs, results output, or interfaces between AI systems). Security risks may be generated by third-party components or other integrated systems and vulnerabilities may not be easily identified by T&E.

MBSE Mitigation(s):

- MBSE can apply automated techniques to identify vulnerabilities within system architectures (e.g., ATLAS™). These vulnerabilities may include a set of mitigations to help inform steps to reduce risk to the system. MBSE models provide a system representation to explore the system design for vulnerabilities and evaluation, including clarifying interfaces that may introduce vulnerabilities.
- One notable cyber challenge for AI models is training data poisoning. T&E professionals can analyze risk by reviewing how the system design restrained outputs of the AIES or approaches output cross validation.
- MBSE frameworks extended to include tools to incorporate threat modeling for cyber T&E enable threat analysis on the operational architecture of a system.

MBSE Mitigations to the T&E of AIES

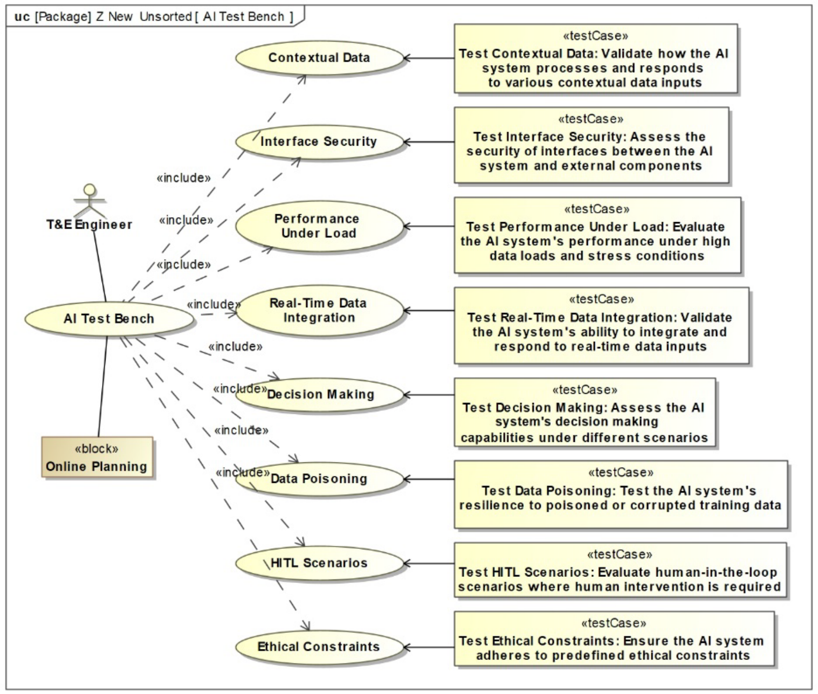
Limited "awareness" (context for decision-making)

T&E Limitation(s):

Testing AIES effectiveness in performing complex tasks performed by humans (e.g., answering questions in a chat stream, making multivariate policy decisions) and their application of "common sense" can be extensive, expensive and require human validation to test use cases.

MBSE Mitigation(s):

- Automated test benches: Created to test how AIES perform with activities requiring "wordly logic" and organized into clear & concise use case diagrams.
  - Test benches can be *generalized, templatized, and stored* in a centralized location so when a new AI model is made or is being retrained, quick tailoring can be done to test that AI appropriately.
  - AI components/capabilities are identifiable (e.g., color highlighting) and well-documented in MBSE better guides the T&E approach.
  - AIES which enable complex human-like capabilities have multiple AI models working in-line or in collaboration and each AI component should be tested both in isolation and in concert with the broader system.
- **Note**: Simply creating a model of an AIES in and of itself will not mitigate the issue of AIES lacking "common sense". Rigorous behavioral testing is still required.



Use Case diagram with example test cases

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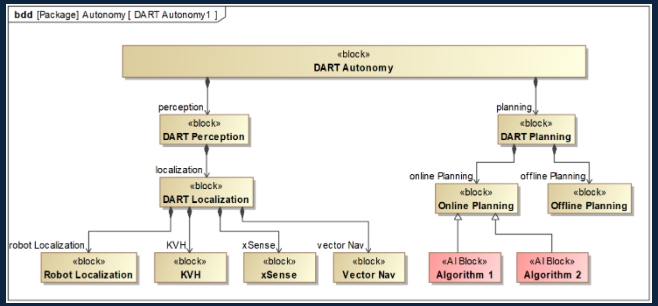
MBSE Mitigations to the T&E of AIES

Leveraging AI Model Transparency



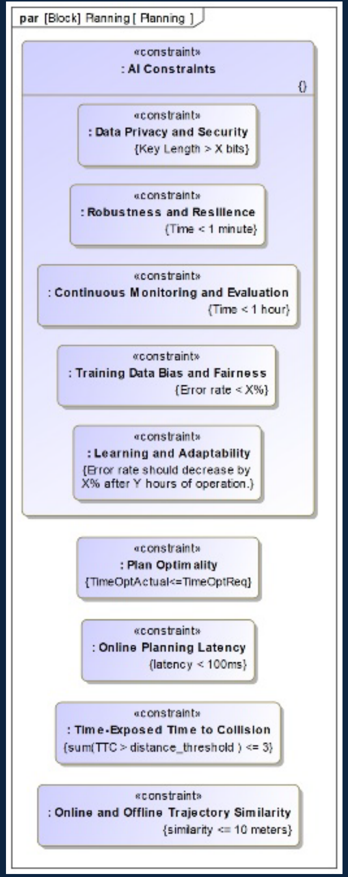
AI Stereotype adornment on BDD

T&E Limitation(s):

Exposing the innerworkings of the AIES enables T&E to more precisely and effectively test the AIES by looking at sub-component and aggregate system performance.

MBSE Mitigation(s):

- MBSE constraints: Leverage AI model transparency by exposing the limits on AI function and behavior to inform conditions needed to be represented in the AI training/test data and evaluated during T&E.
    - Constraints are useful for T&E to assess how well data covers operational conditions or introduces bias. Constraints safeguard an AI component by putting limits on ranges of characteristics of outputs, including *computational* (e.g., GPU), *performance* (e.g., accuracy), and *decision-making* (e.g., confidence) metrics.
    - Clearly documenting these constraints in a Parametric diagram aids T&E on facets of the AIES that will likely need to be *retested* (ideally automated) over the full lifecycle.
- Model Specification/Stereotypes: In cases where greater transparency is granted on the AI component, it can be noted in the model specification details the type of AI model (e.g., LLM, Computer Vision), what library it was derived from (e.g., Gemini, Midjourney, ChatGPT), what training dataset was used, and what additional data the component has ingested deployment.
    - If new data types are required, MBSE allows for further extension through the usage of *stereotypes*.



Example AI Constraints

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SysML to DoDAF and UAF Alignment

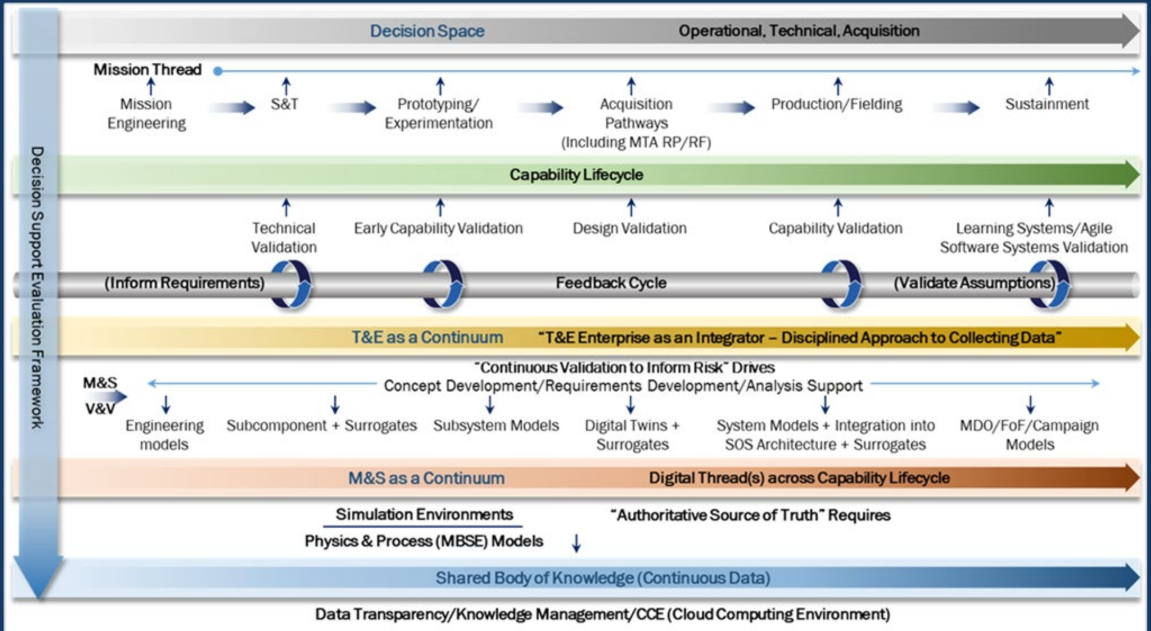
The example use case diagram recommendations, developed within SysML, can be translated to other frameworks.

Systems Modeling Language (SysML)	Department of Defense Architecture Framework (DoDAF)																			Unified Architecture Framework (UAF)										
	CV's	CV-5	DIV's	DIV-2	OV's	OV-1	OV-2	OV-4	OV-5a	OV-5b	OV-6b	OV-6c	SV-1	SV-2	SV-4	SV-5	SV-7	SV-10b	SV-10c	Taxonomy (Tx)	Structure (Sr)	Connectivity (Cn)	Processes (Pr)	States (St)	Interaction Scenarios (Is)	Information (If)	Parameters (Pm)	Constrains (Ct)	Summary & Overview (Sm-Ov)	Requirements (Req)
Activity Diagram										X					X	X							X							
Block Definition Diagram	X		X			X	X	X	X				X	X						X	X					X	X	X	X	
Internal Block Diagram							X							X							X	X								
Parametric Diagram																	X											X		
Requirement Diagram/Table		X		X																										X
Requirements Matrix					X																									X
Sequence Diagram												X							X						X					
State Machine Diagram											X							X						X						
Use Case Diagram/Matrix						X									X															

More research is planned to translate these recommendations into additional MBSE architectures beyond those already highlighted and to provide further examples.

Conclusions and Next Steps

- MBSE for T&E of AIES is an example of the value of end-to-end Digital Engineering
  - ➢ Aligned to and enables DTE&A's developmental Test and Evaluation as a Continuum.[1]
  - ➢ Potential risks associated with AI Model integration, operational employment, cybersecurity resilience, user adoption, and AI model sustainment can be identified, thereby enabling more effective T&E.
- Planned Future Work
  - ➢ Measure the utility of each of the recommendations for T&E professionals evaluating AIES.
  - ➢ Explore more complex AIES implementations (e.g., multiple AI models working together) and further MBSE enablement opportunities.
  - ➢ Prototype tools that can automate the processing of AI data in an MBSE product into T&E information and/or application of T&E to AIES.
  - ➢ T&E of AIES Policy is being reviewed to ensure enablement for AIES.



C. Collins and K. Senechal, "Test and Evaluation as a Continuum," *The ITEA Journal of Test and Evaluation*, vol. 44, no. 1, 2023.

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Research Team

Thank you!

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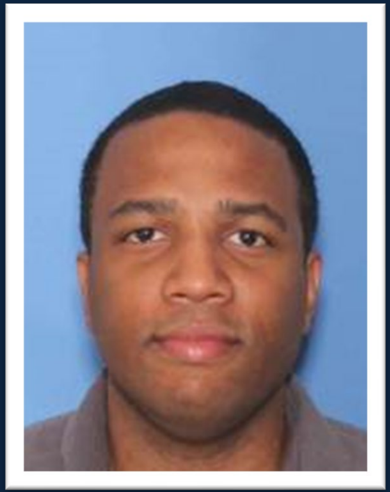

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