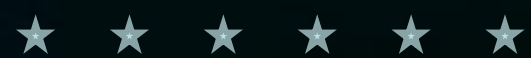


# TSA Machine Learning Opportunities

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Transportation  
Security  
Administration



# Machine Learning at TSA

## Objective

To provide an overview of ORCA's Requirements and Architecture Division (RAD) development and interest in Machine Learning and to discuss Machine Learning opportunities and developments for TSA Transportation Security Equipment (TSE).



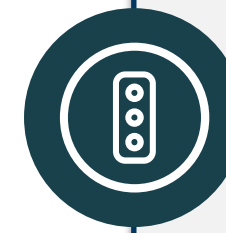
Different factors within TSA's background enable Machine Learning opportunities for Industry



Machine Learning impacts TSA's Risk Mitigation Trade Space



Data Collection, Stream of Commerce (SoC) and ground truthing efforts including SoC meta data



Stakeholders may face challenges and mitigations when working on current and new Machine Learning opportunities

Proposals can be submitted through The TSA Innovative Concept Broad Agency Announcement (TSIC BAA) HSTS04-14-R-BAA004 on [FedBizOpps](#).



# Background and Operational Context

In the wake of the September 11 attacks, TSA was created to strengthen the security of the nation's transportation systems. TSA provides capabilities that drive national security across transportation modes and screen all commercial airline passengers and baggage while ensuring the freedom of movement for people and commerce.

➤ TSA operates **365 days a year** across roughly **440 federally regulated airports**

➤ On any given day, TSA and industry partners secure:

➤ **2 million passengers**

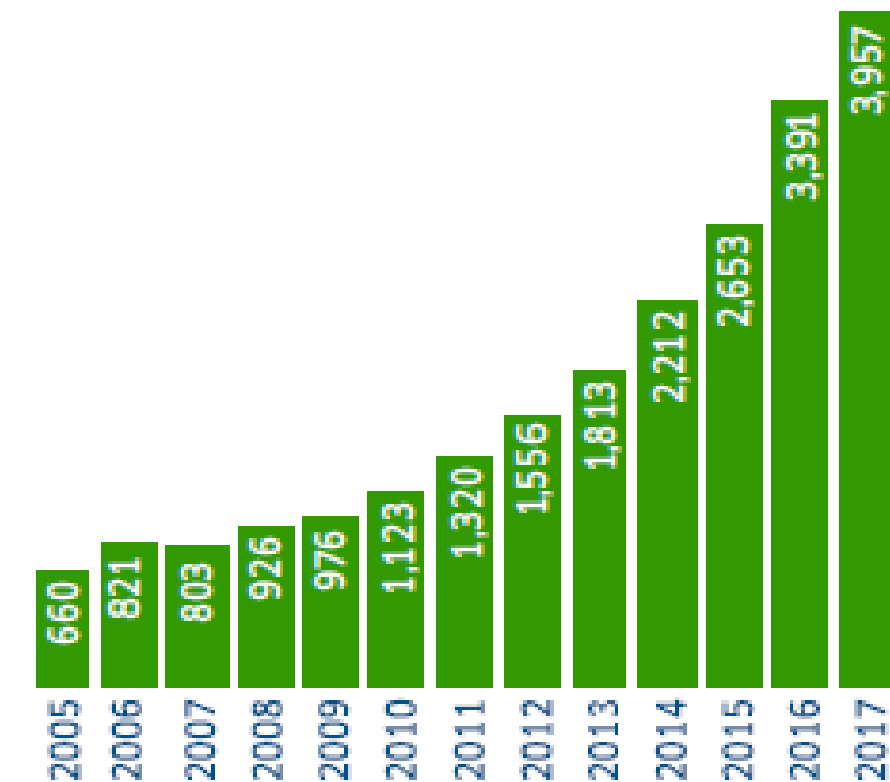
➤ **1.3 million checked bags**

➤ **4.9 million carry-on bags**

➤ **10 billion pounds of cargo**

➤ In addition to evolving security threats, the Federal Aviation Administration forecasts U.S. passenger growth at an average of ~2 % per year, which will require TSA to secure and protect an increasing number of flights.<sup>1</sup>

Firearm Discoveries Since 2005



The increase in commercial aviation traffic, coupled with continuing terrorist threats, requires TSA to continually assess the effectiveness and efficiency of security screening to ensure the best use of limited resources.

[1] [https://www.faa.gov/data\\_research/aviation/aerospace\\_forecasts/media/FY2018-38\\_FAA\\_Aerospace\\_Forecast.pdf](https://www.faa.gov/data_research/aviation/aerospace_forecasts/media/FY2018-38_FAA_Aerospace_Forecast.pdf)

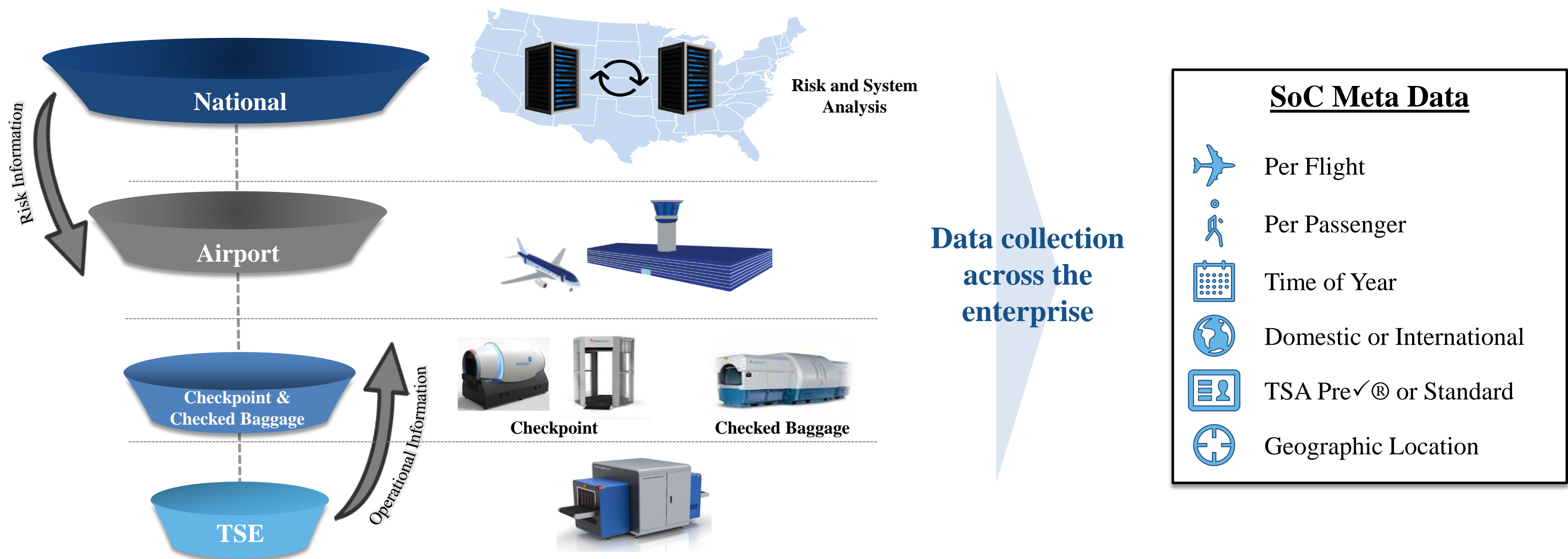
# TSA Machine Learning Opportunities

Machine Learning has the potential to impact TSA across the trade space and enable improved Test and Evaluation (T&E) and requirements development processes.



# Stream of Commerce Data Collection

Large quantities of SoC and associated meta data from across TSA's enterprise is required to enable the success of Machine Learning. Collected images and related data will be used by TSA Headquarters for enterprise level risk and system analysis as well as OEM and 3<sup>rd</sup> party algorithm development purposes.

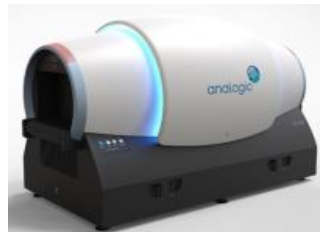




# APSS T-BAA Window 1 and Additional Scope

## Window 1

In support of advancing security screening capabilities, the ORCA released the Accessible Property Screening Systems (APSS) T-BAA Window 1 for mature CT based systems in August 2017. The T-BAA resulted in 4 OEMs developing enhanced detection capabilities to support APSS Detection Standard 6.1.



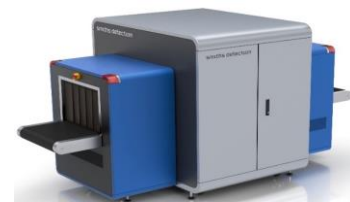
Analogic ConneCT



IDSS DETECT 1000



L-3 ClearScan

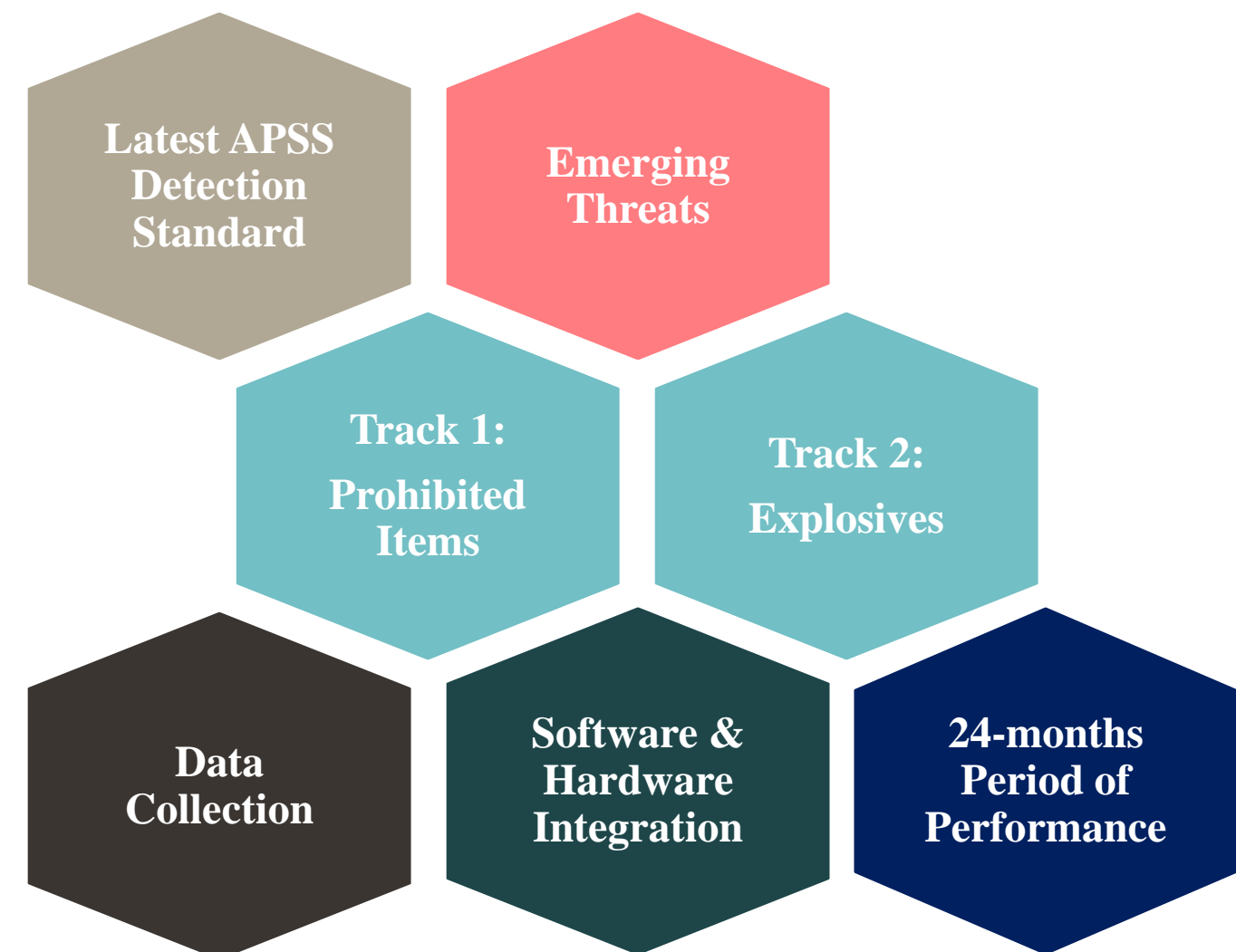


Smiths Detection Hi-Scan 6040CTiX

Targeted Broad Agency Announcement (T-BAA) HSTS04-17-R-BAA226 for APSS Window 1- CT can be reviewed on [FBO](#).

## Additional Scope

TSA aims to use Machine Learning to build on the progress and momentum of previous developmental efforts (APSS Window 1) to incorporate Prohibited Items (PIs) and detection of new explosive materials. Solutions are to be deployable to checkpoint CT systems and operationally feasible.



# Challenges and Path Forward

To ensure the success of Machine Learning initiatives **it is essential that TSA and the industry collaborate** to address challenges and leverage industry advancements. Data, data storage and transfer, standardized interfaces, and computational power are key foundational focus areas to enable Machine Learning implementation.

## Challenges

### Data

- Machine Learning algorithms will require large quantities of threat and SoC data for training and development

### Data Storage and Transfer

- Collected data will need to be stored and made accessible to OEMs and 3<sup>rd</sup> parties during training, development, and testing

### Computational Power

- Machine Learning algorithms may require additional computational power due to their size and complexity

### Standardized Interfaces

- OEMs utilize proprietary image formats and interfaces which poses challenges for 3<sup>rd</sup> party integration

### Requirements and Productization

- Requirements need to be defined for vendors to finalize designs and upgrades

## Path Forward

### Data

- Coordination with OEMs and 3<sup>rd</sup> parties to determine the optimal quantity of images and development of a data collection and management strategy

### Data Storage and Transfer

- Establish a common database to store SoC and threat images to ensure data availability

### Computational Power

- Coordinate with OEMs and 3<sup>rd</sup> parties to determine the computational requirements

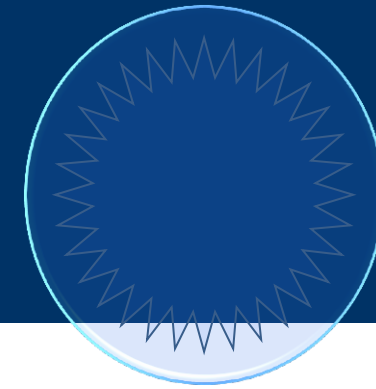
### Standardized Interfaces

- Standardize data formats and interfaces to enable rapid integration of innovative 3<sup>rd</sup> party solutions

### Requirements and Productization

- OEMs provide hardware and software upgrades for procurement in accordance with the requirements

Questions



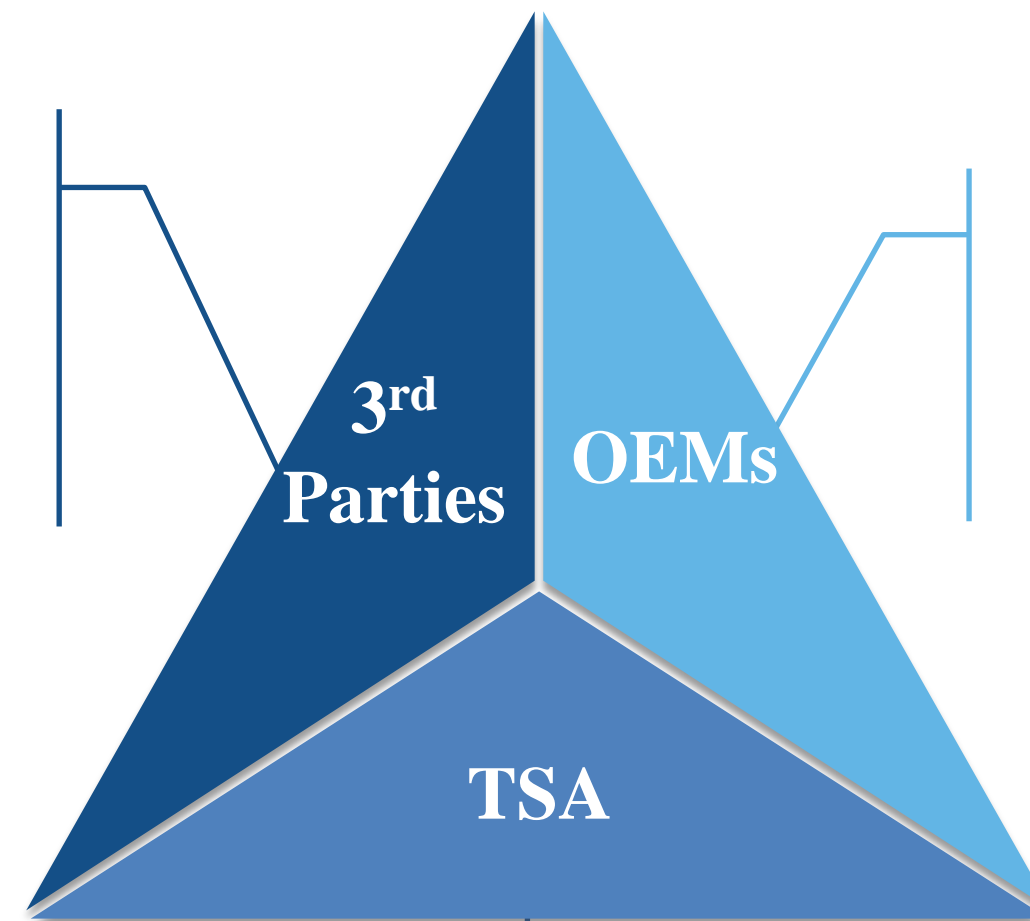


# Appendix

# OEM and 3<sup>rd</sup> Party Partnerships

TSA values and requests **partnerships** between the OEMs and 3<sup>rd</sup> party vendors to promote innovative solutions. Collaborations will lead to advanced machine learning algorithms to further improve the detection capability.

Provides Machine Learning expertise and innovative solutions that can be leveraged to dramatically enhance traditional detection capability



Provides Checkpoint CT and integration expertise to ensure overall solution(s) is fieldable and meet TSA requirements

Provides operational context and outlines requirements and objectives for OEMs and 3<sup>rd</sup> parties

# Aviation Security – Current and Future State

In order to address increasing security and operational pressures, aviation security must continue to evolve to effectively and efficiently detect a wider range of threats.

## Present

Transportation Security Officers (TSO) review x-ray images of every carry-on bag

Passengers divest liquids, aerosols, gels (LAG), laptops, bulky outer garments, and shoes

Passengers stop and pose for Advanced Imaging Technology (AIT)

High system Probability of False Alarm (Pfa) leads to long wait times

Passengers are screened at Standard or Pre ✓ Lanes

Transportation Security Equipment (TSE) software, algorithms, and data managed locally

Variation among TSE user interfaces increase complexity and training requirements

Unique TSE designs and interfaces result in long capability development lead times

## Future

Enhanced Automated Threat Recognition (ATR) of explosives, weapons, and contraband

Minimal divestiture of LAG, laptops, and clothing increases throughput

Passengers move through checkpoint at a walking pace in parallel with carry-on items

Reduced Pfa to increase screening efficiency

Risk Based Security (RBS) enables dynamic screening, more efficient allocation of resources

TSE securely networked and communicating via Security Technology Integrated Program (STIP)

Common Graphical User Interface (GUI) yields consistent user experience across TSE fleet

Open Architecture and Application Program Interfaces (APIs) enable modular “plug and play”



# Considerations

As the threat's landscape is continuously evolving, TSA is seeking innovative approaches to enhance security effectiveness while improving operational efficiency. Here is a list of considerations for data collection, material discrimination, and resource constraints.

## Material Discrimination

**Consideration:** Detection at lower mass requires new approaches to improve false alarm rates  
**Mitigation:** Need a suite of algorithms to support material discrimination

## Data Collection

**Consideration:** The amount of images required for successful Machine Learning is much greater than traditional approaches  
**Mitigation:** OEMs, third parties, and TSA to work together to determine the optimal image quantity and data collection strategy

## Data Interfaces

**Consideration:** Partnership with OEMs and third party organizations will require standardized interfaces and standardized data formats  
**Mitigation:** Continue development and adoption of common data interfaces and formats to facilitate third party integrations. TSA requires OEMs to comply with Digital Imaging and Communications in Security (DICOS) format.

## Resource Limitations

**Consideration:** Developing Machine Learning algorithms concurrently for explosives and PI may cause vendor resource constraints  
**Mitigation:** The project timeline of 24 months allows for staggered work so OEMs and third party organizations can focus on two different tracks