Functional Hazard Analysis (FHA) and Subsystem Hazard Analysis (SSHA) of Artificial Intelligence/Machine Learning (AI/ML) Functions within a Sandbox Program

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Motivation: Naval Ordnance Safety and Security Activity (NOSSA) Investigating Policy and Guidelines Specific to AI/ML Functions





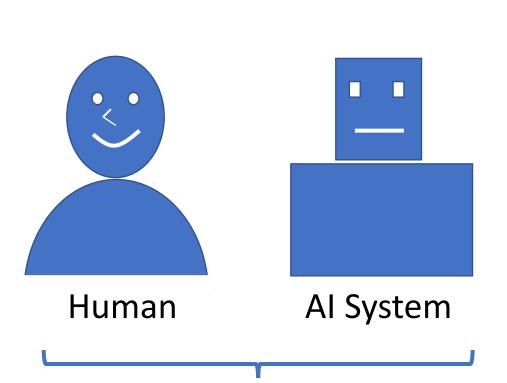
The strength of AI is also its weakness!



AI/ML is a New Development Paradigm

When expected to successfully perform critical tasks, the **Human** needs the "*right/correct*" *training* and *incentives* to consistently meet expectations.

Expectations need to define a *likelihood* that he/she will be successful *most of the time*.



When expected to successfully perform critical tasks, the **Al System** needs the "*right/correct*" *training* and *algorithm* to consistently meet expectations.

Expectations need to define a *likelihood* that the machine will be successful *most of the time*.



This comparison "right/correct" training analogy applies to AI developed code but not traditional code.



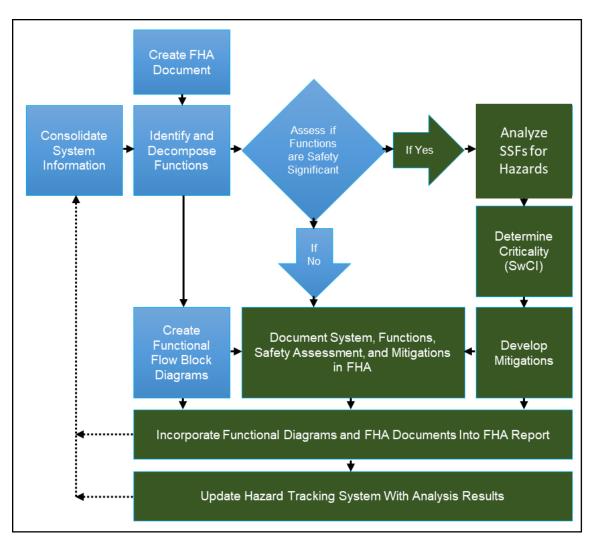
Basic System Safety definitions:

- Software Control Category (SCC) -- A numeric number resulting from applying a standard method to categorize safety significant software based on its level of autonomy.
- Software Criticality Index (SwCI) -- A numeric number resulting from a combination of SCC and severity to determine the LOR tasks required for safety significant software.
- Level of Rigor (LOR) -- per MIL-STD-882 "A specification of the depth and breadth of software analysis and verification activities necessary to provide a sufficient level of confidence that a safety-critical or safety-related software function will perform as required." A specific set of tasks to be completed before that safety significant software is considered "safe" or representing a certain level of acceptable risk for the system.
- Functional Hazard Analysis (FHA) The primary analysis used to determine SCC and SwCI determinations for safety significant software. Each function is evaluated for level of autonomy and safety criticality.
- Subsystem Functional Hazard Analysis (SSHA) A detailed subsystem analysis used to determine LOR for safety significant software.





FHA Workflow Conducted by System Safety Practitioners







Stakeholder's Analysis Table (Subset of List)

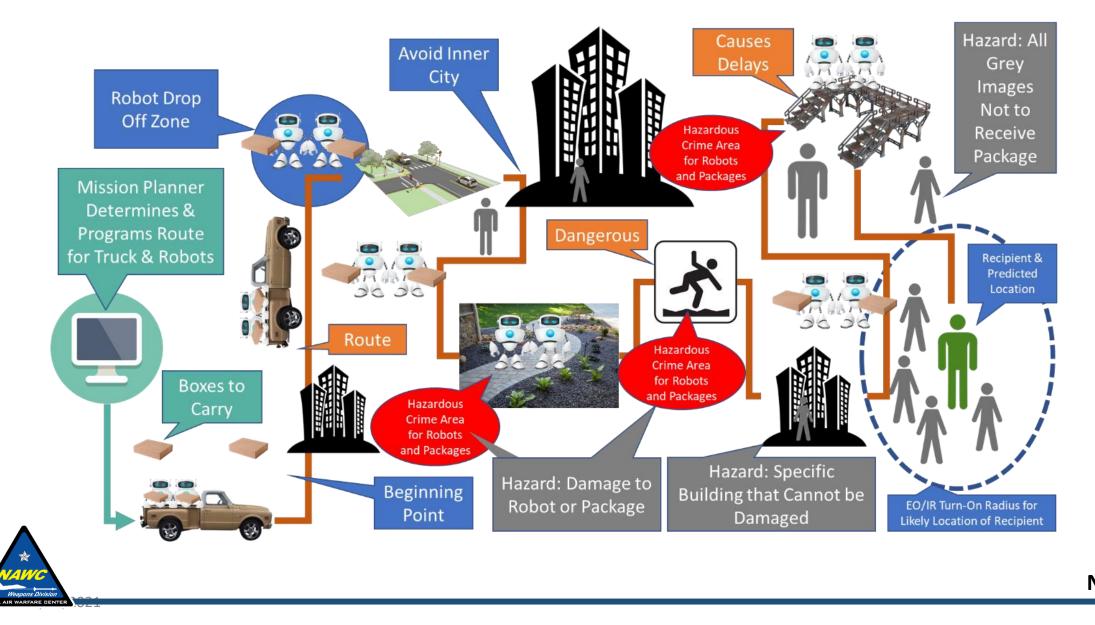
	Name/Organization	Туре	Want/Need	Concern/Loss
9	NOSSA	Sponsor	What tools, guidance and documentation would need to be created to support the processes and policy per each group's needs? Groups: Developers need from system safety, System safety practitioners from system safety and Oversight folks from system safety.	NOSSA: Unsafe deployed system
10	NOSSA	Sponsor	Along with the processes, what analytics need investigation for each user group?	NOSSA: Unsafe deployed system
11	NOSSA	Sponsor	How would various AI/ML software designs affect the analytical approach?	NOSSA: Unsafe deployed system
12	NOSSA	Sponsor	What kind of OQE is required per a given AI/ML technique and implementation structure to support a program moving forward?	NOSSA: Unsafe deployed system
13	NOSSA	Sponsor	Will data and analytics be considered as separate pieces to inspect?	NOSSA: Unsafe deployed system
14	NOSSA	Sponsor	During a WSESRB or Technical Review Panel review that involves AI/ML, how would systems, data and numbers be presented to allow for proper investigation and analysis to ensure contextual accuracy based on group technical background?	NOSSA: Unsafe deployed system
15	NOSSA	Sponsor	What are the factors and limitations associated with confidence of numbers presented regarding AI/ML performance?	NOSSA: Unsafe deployed system
16	NOSSA	Sponsor	AI/ML performance is always associated within the context of the training data?	NOSSA: Unsafe deployed system
17	NOSSA	Sponsor	What does it mean to perform architecture, design, or code analysis (see MIL-STD- 882E Table V) with an AI/ML system, especially when, for example, even the developer has limited understanding on how the neural network works?	NOSSA: Unsafe deployed system



Note: NOSSA is investigating software safety processes to appropriately address ML/AI.

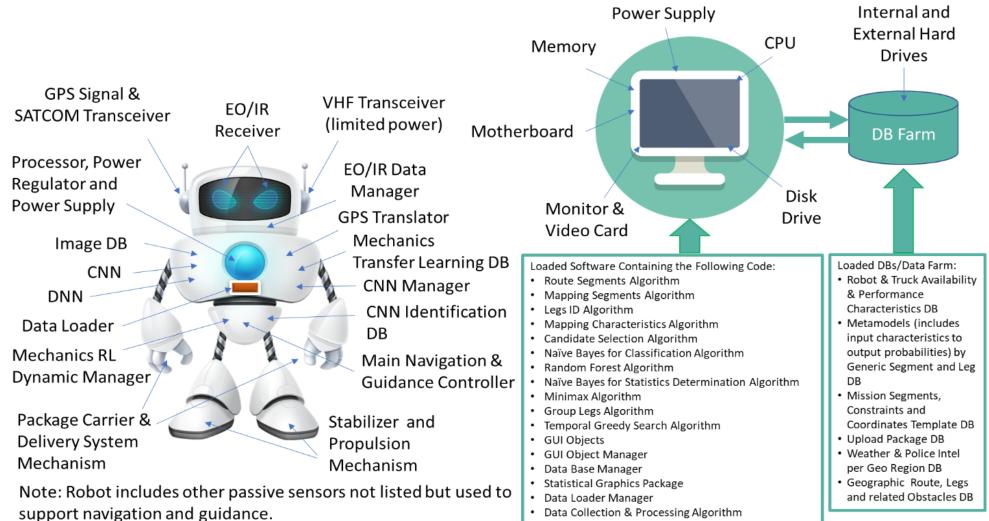


Operational Use Case of Two Robots Delivering Packages



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Robot and Mission Planner Subsystems







Al Type Definition

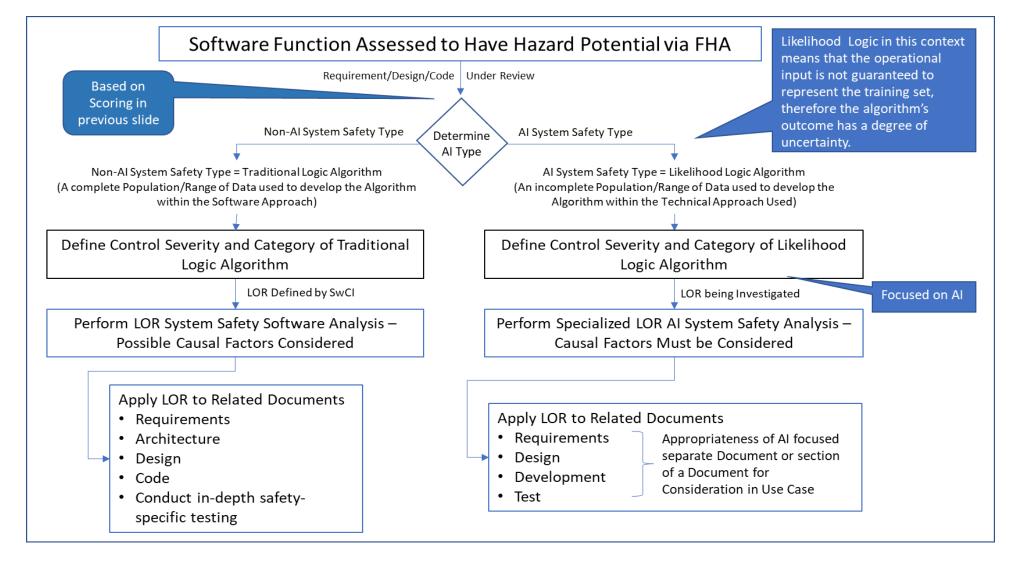
Al Type (Working Definition): For system safety concerns, an Al Type of function means that an algorithm will be developed:

- (1) from using data approximations to build its algorithm, e.g. from simulations and synthetic data vs an equation that accurately represents real world physics, and/or
- (2) when data samples used to build its algorithm is a subset of the actual population size, e.g., training data samples from population to support machine learning, training data samples requiring clutter backgrounds.

AI Type Examples of Specific Algorithms	Algorithm built based on using data approximations	Algorithm built based on using data samples from larger population	Final Score
CNN	x (if synthetic data used for CNN)	x (training data samples)	0 to 2
DNN + SL	x (if synthetic data used for DNN)	x (training data samples)	0 to 2
DNN + RL	x (if synthetic data used for DNN)	x (training data samples)	0 to 2
RNN (LSTM)	x (if synthetic data used for RNN)	x (training data samples)	0 to 2
RNN (Simple)	x (if synthetic data used for RNN)	x (training data samples)	0 to 2
Naïve Bayes	x (if modeling and sim data used to produce statistics for Naïve Bayes)	x (if RL used during opponent interaction to train algorithm)	0 to 2



Flow to Assess AI Type using Special FHA and SSHA Rigor







FHA Example for Mission Planner from Sandbox

Each Column represents a recommendation

Recommendations 1, 2 and 3

Haz ID #	Phase	Activity	State/ Mode	1	Function	Functional Failure	Hazard T	itle	Hazard Description		AI Type Scoring	AI Type Justification	Al Type Autonomous Justification	System Item(s)	Causal Factor Description		
	Test & Deployment	Metamodel Selection	Setup	Mission Planner - Route/Robot F Selection (Naïve Bayes				t Function Unavailable	No hazard since no will be selected	metamodel			2				
				Metamodel		Function Malfunctions (degraded, partial, or unexpected results of the function, signal too small/strong/intermittent)	Wrong Metamodel		f a wrong metamodel selected, then the wro could be selected resu backages not being del being too early or late delivered to wrong rec the package could be lu Assumption: Package delivered means packa ost - Catastrophic haza	ng robots Iting in Iivered or and so reipient, or ost. not age will be	ii c t a s	nput to function has nfinite number of ombinations - no raditional pproximation is ufficient	Semi-Autonomous Man in Loop for approve of route	Aission Planner	Training Data is incorrect or incomplete, corn case occurence		
							not selected at the sequence then rou will not progress.	right ite selection									
						(too early, too late, outside	No hazard since fu only relevant at a c sequence, not time	ertain									
			Mi	shap	Effects	Existing Mitigations	Software Control Category (SCC)	Criticality Ind	ex Software Criticality Index (SwCl)		Recommended Mitigations	Component(s)	Follow-On Actions	Comm	ents		
	Contin	ued	Deliverin package wrong re could be catastroy the mate hazardor very valu	to the Equ ceipient bhic since trial is us and/or	uipment Loss outp oper 2. Te	perator review of this function ut is required before system ations can progress st Data is used to ensure ML is prehensive	2- Semi- Autonomous	1	SwCl 1	used for sele selected item from next cho or select defa	t threshold on propotionality ction e.g. if propotionality of i is not significantly different oice (10x), then declare fault uult metamodel. redundant, inde pendent non that review route/robot compatibility	Data Manager Database Farm Graphics User Interface ((recommended mitigations if 3UI) possible	Jser review of this function before the system can pro- user must approve of the r ncluding compatability be oute. With a trained user, and appropriate time wind approval, the user increase Autonomous) to 2 (Semi- he lack of other redundar further increase the SCC. In ecommended mitigations	gress operation. The oute/robot selection, tween robot and detailed procedures, ows for review and is the SCC from 1 Autonomous), though t interlocks does not mplementing of		

SSHA for Meta-Model Selection Algorithm within Mission Planner from Sandbox

Haz ID#	Phase	State/ Mode	System	Subsystem	Component	Element	Hazard Title	Hazard Description	Causal Factor Description	Mishap	Effects	Existing Mitigations
Identifier used to reference specific hazard.	Multiple phases can	The State and/or Mode of the system for the hazard of concem.	The composite at any level of complexity of interworking parts (personnel, procedures, equipment, hardware, software, et al) used together to perform a task or accomplish a mission.	system	A functional or physical portion of a sub system designed, used or integrated to accomplish one aspect of the sub system task or objective.	A functional or physical portion of a component designed, used or integrated to accomplis h one aspect of the component	Short title of the hazard	The detailed description of the conditions under which hazardous energy may be released in an uncontrolled or inadvertent way.	The detailed description of the failures, conditions, or events that contribute either directly or indirectly to the existence of the hazard.	The event or series of events where haz ardous energy release could negatively effect equipment, personnel or environment; accident	The results of the mishap to include injury or death, damage to equipment and property, or damage to the environment.	Controls that are already planned existing to mitigate the risk.
SSHA-001	Test & Deployment		Mission Planner				AI Function for metamodel selection (Naive Bayes) failure			Delivering the package to the wrong receipient could be catastrophic since the material is hazardous and/or very valuable.	Personnel Injury / Equipment Loss	
									Incorrect algorithm selection			
									Improper curation of data			Multiple sources (primary, secondary and tertiary sources) accommodate sources that fail/missing.
									Too much or too little data (Underfitting and Overfitting of model)			



SSHA LOR Table Example Based on Data Flow Analysis of Meta-Model Selection within the Mission Planner

		_		Primary	Support		Softwa	tware Criticality Index (SwCl) Representative Artifacts			Representative Artifacts
evel or Rigor (LOR) Activity	Phase	Focus	LOR Description	Responsibility	Responsibility	Baseline	4	3	2	1	Produced
			Would the corruption of API/MSG/SQL/Other affect data variations requiring additional training of the Target Algorithm?	Al/ML Algorithm Developer	Data Analytics Engineer						Data Analytics Report
			If so, will quality (composition/complexity/structure) of Training Data significantly increase? Explain specific to the API/MSG/SQL/Other.	AI/ML Algorithm Developer	Data Analytics Engineer						
			Will these variations be part of the analysis for selecting the "best" algorithm? Explain.	AI/ML Algorithm Developer	Data Analytics Engineer						
		API/MSG/SQL Interface	Because of this issue, will quantity (more instances) of Training Data significantly increase? Explain specific to the API/MSG/SQL/Other.	Al/ML Algorithm Developer	Data Analytics Engineer			R	R	R	Data Analytics Report
			Will creating/finding enough training data replicating the corruption be an issue? Explain.	Al/ML Algorithm Developer	Data Analytics Engineer		ess of LOR	or require	nt – Requii d in order		Data Analytics Report Training Data Curation Report Training Data Curation Report
LG6: Data Flow Analysis for le Mission Planner	Algorithm Design, Algorithm Code and Test and Evaluation		Are you confident that any additional data created/found will adequately represent the effects associated with replicating the corruption? Explain.	Al/ML Algorithm Developer	Data Analytics Engineer	AD: As o AD: As o R: Requ IV&V: In Validati	ired for as ndepender	Custome signed LOI	R		
			Based on Modality Table: Describe Data Source Precedent for Improving Success Rate (ranking of primary, secondary tertiary n attributes) by addressing related question in the table.	Al/ML Algorithm Developer	Data Analytics Engineer	• N/A: No		ole for this	program o	or LOR	Training Data Curation Report
		During Deployment & Curation	Based on Modality Table: Describe how missing and sparse data issues are modeled by addressing related question in the table.	Al/ML Algorithm Developer	Data Analytics Engineer			R	R	R	Training Data Curation Report
		Congruency	Based on Modality Table: Describe how the quality of Training Data Characterized by addressing related question in the table.	Al/ML Algorithm Developer	Data Analytics Engineer						Training Data Curation Report
			Based on Modality Table: Describe how the quantity of Training Data Characterized by addressing related question in the table.	Al/ML Algorithm Developer	Data Analytics Engineer						Training Data Curation Report



Investigation Questions Based on Modality

Investigation Topic	(Modality 1) multiple data sources, where each source contains one or more attributes	(Modality 2) single data source containing multiple data attributes, e.g., CNN	(Modality 3) combination of multiple data streams, where each stream contains one or more attributes and from a single data stream containing multiple aggregated data attributes, e.g., Naïve Bayes aggregated with CNN
Describe Data Source Precedent for Improving Success Rate (ranking of primary, secondary tertiary n attributes)	Which sensor, communication link or human input content elements take precedent over others for improving success rate when training the ML algorithm under normal to stressed operational conditions?	Which attributes within the single data source take precedent over others for improving success rate when training the ML algorithm under normal to stressed operational conditions?	What data source content is more significant with regard to normal to stressed operational conditions? When dealing with separate streams, which sensor, communication link or human input content elements take precedent for improving success rate when training the ML algorithm under normal to stressed operational conditions? When dealing with combined streams, which attributes within the single data source are identified as primary, secondary and tertiary regarding importance for ML algorithm to improve success rate under normal to stressed operational conditions?
Describe how missing and sparse data issues are modeled	How is sensor malfunction, message corruption and human input errors on the higher precedent attributes forcing lower level attribute mixes of training data to ensure algorithm can deal with "real" operational issues?	Corruption in parts of image, especially containing higher precedent attributes forcing secondary and tertiary attribute mixes of training data to ensure algorithm can deal with "real" operational issues.	Combinations on modalities 1 and 2 regarding training of algorithm to deal with "real" operational issues.
Describe how the quality of Training Data Characterized	What is the precedent list (from highest to lowest) of attributes being used for training.	Same as Modality 1 for this row.	Same as Modality 1 for this row.
Describe how the quantity of Training Data Characterized	How much more emphasis Is placed on quantify of training data variations that have higher precedent than lower?	Same as Modality 1 for this row.	Same as Modality 1 for this row.





References

Brose, C. (2020): The Kill Chain, Defending America in the Future of Hi-Tech Warfare, Hachette Books, New York.

National Defense Authorization Act (NDAA) Fiscal Year 2021. Section C Artificial Intelligence and Emerging Technology.

National Security Commission on Artificial Intelligence (NSCAI). (2021). Draft Final Report. Autonomous Weapon Systems and Risks Associated with Al-Enabled Warfare. Chapter 4. <u>https://www.nscai.gov/wp-content/uploads/2021/01/NSCAI-Draft-Final-Report-1.19.21.pdf</u>

Naval Sea Systems Command. (2008) Department of the Navy Weapon Systems Explosives Safety Review Board (NAVSEAINST 8020.6E)

National Institute of Standards and Technology (NIST). (2019). U.S. Leadership in AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools. <u>https://www.nist.gov/system/files/documents/2019/08/10/ai_standards_fedengagement_plan_9aug2019.pdf</u>

Joint Software Systems Safety Engineering Workgroup. (2017) Software System Safety Implementing Process and Tasks Supporting MIL-STD-882E (JS-SSA-IF Rev. A). Washington, D.C.: Pentagon.

Shodani, S., (2018) Opinion: A summary of Concrete Problems in AI Safety. <u>https://futureoflife.org/2018/06/26/a-summary-of-concrete-problems-in-ai-safety/</u>

Joint Services – Software Safety Authorities (JS-SSA). (2017). Software System Safety Implementation Process and Tasks Supporting MIL-STD-882E (JS-SSA-IG Rev. A).

Defense Standardization Program Office. (2012) System Safety (MIL-STD 882E). Washington, D.C.: Pentagon.

National Security Commission on Artificial Intelligence (NSCAI). (2019). Final Report. Establishing Justified Confidence in AI Systems. Chapter 7.

Radio Technical Commission for Aeronautics (RTCA). (2012). Software Considerations in Airborne Systems and Equipment Certification. (DO-178C). Washington D.C.: Federal Aviation Administration.

DoD Architecture Framework Version 2.02. DoD Deputy Chief Information Officer. <u>https://dodcio.defense.gov/library/dod-architecture-framework/</u>

Dam, S. (2006) DoD Architecture Framework A Guide to Applying System Engineering to Develop Integrated, Executable Architecture, SPEC.

Booch, G., (2017): Unified Modeling Language User Guide 2nd Edition. Addison-Wesley Professional.



Hastie, T., Tibshirani, R., Friedman, J. (2017) The Elements of Statistical Learning Data Mining, Inference and Prediction. Second Edition. Springer.