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# AI-Driven Expert Modeling for Cognitive Assistance in Anti-Submarine Warfare

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**Abstract**—Anti-Submarine Warfare (ASW) missions are becoming more complex with the increase of: i) collaboration between platforms, ii) multiple underwater platform types, iii) volume of data, vi) underwater sensor resolution, and v) challenges in detecting enemy submarines. Such complex and uncertain environments engender potential for cognitive overload and human error, leading to reduced situation awareness and detection performance. The objective of this work is to improve Human-Machine Interface through the use of a decision-support system for ASW crew, especially focusing on the sonar operator, sonar coordinator and underwater warfare officer roles. It aims at helping sonar operators taking the right decision at any decisive moment without disturbing the ASW drill. The use case investigated here focuses on modeling expert decision-making processes for determining active sonar transmitter/receiver immersion parameters. Policy capturing is a method which allows training models based on expert decision-making to infer and reproduce their judgment patterns. In this paper, we demonstrate how we incorporated a full-machine learning pipeline for ASW sonar parameter predictions based on cognitive modeling. Our study was able to generate a first proof-of-concept model based on supervised multi-output machine learning algorithms: Decision-tree, Linear-Regression, Random-Forest and K-Nearest Neighbour. Our work demonstrates the possibility of predicting sonar setting with accuracies up to and higher than 80% by using an online multi-model frugal learning approach requiring only a few hours of querying to efficiently capture expert decision patterns.

**Keywords**—Multi-output machine learning, Policy-capturing, Frugal learning, Decision-support system, Anti-submarine warfare.

## I. INTRODUCTION

Extracting expert knowledge for configuring decision support systems (i.e. expert systems) has been a long-standing challenge in cognitive engineering [1]. A key issue is that verbal descriptions of one's own decision process may be biased and incomplete, due in part to the difficulty of becoming fully self-aware of implicit, procedural, or non-verbal knowledge. One solution for that is to infer experts' judgment policies using supervised machine-learning techniques based

on either historical or hypothetical cases. Once learned, an inferred decision policy can be used to bootstrap human decision making in real-time dynamic environments to avoid potential errors that may be due to mental overload, fatigue, stress, or distraction [2]. A cognitive system can be described as a goal-oriented agent that uses knowledge about its environment to execute a specific task, and adjust its actions based on the goal. Humans are considered cognitive systems; yet advances in computational neuroscience technology and automated systems have started to help humans support their cognitive abilities and result in the development of so-called artificial cognitive systems: "systems that perform tasks normally associated with human cognition", and joint (human-machine) cognitive systems [3].

Such a development of decision-support systems (DSS) or operator aids is becoming crucial in the underwater warfare domain, which might answer some of the challenges the sonar operator, sonar coordinator and underwater warfare officer roles deal with [4-5]. Indeed, research shows that these operators often face cognitive challenges pertaining to attention deficits and fatigue [6]. In addition to operational efficiency improvement, it is also particularly relevant regarding knowledge sharing between operators, experienced and novice, as crew turnover is a key concern for all worldwide navies. Moreover, training centers could take advantage of such AI-powered technologies for enabling digital tutoring techniques. Previous work has also been targeting the development of DSS for anti-submarine warfare (ASW) mission management [7], tactical coordinator officer [8] and supporting commander decision-making within ASW context, which are crucial for enhancing mission effectiveness and survival of naval vessels [6]. For example, the Office of Naval Research (ONR) and the Defense Advanced Research Project Agency (DARPA) have been deploying significant efforts towards decision aids in naval and air ASW [7]. However, relatively little attention has yet been placed on the integration of policy-capturing and expert-modeling methods for naval defense decision-support applications [9-11].

## II. POLICY CAPTURING FOR ASW

### A. Expert Modelling

Cognitive Shadow is a policy capturing DSS developed by Thales Research and Technology Canada in collaboration with Thales Defense Mission Systems France and with several academic partners, which enables the automatic online learning of artificial intelligence (AI) models based on expert knowledge [12]. This approach differs from data-mining methods that require large amounts of data to discover hidden relationships (e.g. use of a neural network for mission planning for ASW) [13]. Policy capturing focuses on constrained-complexity models set to learn human expert decision/behavior/judgment patterns (without overfitting noise). The approach enables training models based on very small amounts of data, drawing from existing frugal-learning techniques [12]. Indeed, sparse data is often a major issue for AI within the defense industry, with very limited amounts of open or available data due to sensitivity and distribution restrictions. This tool enables to capture decision patterns from experts.

As for ASW use cases, it can provide to sonar operators recommendations about sonar settings, more specifically most appropriate immersion about the Transmitter (Tx) and Receiver (Rx) arrays. The model is trained on expert reasoning and previous decisions of realistic operational data specific to ASW. This tool could facilitate and enhance human-machine interaction within an ASW complex environment, increasing operational efficiency, simplifying and accelerating decision making and minimizing cognitive overload, bias and risk of error [14-15]. Moreover, one of the challenges with such a system is to help overcome the difficulty with diverging expert judgments: How can we best reconcile different answers from experts about sonar settings in a given context in order to create an effective group-of-experts model?

### B. Anti-Submarine Warfare and Sonar Operations

Sound waves are a major medium of information transmission in ASW due to high conductivity and speed of transmission. Underwater signals are highly exploitable as they are composed of sound waves within which vibration helps propagation even better than aerial propagation and transmission [16]. Sonar is an acronym for sound navigation and ranging (SONAR): sonar systems are a key component of ASW vehicles as it enables the extraction of highly important information for tactical decision within naval and underwater warfare environments. This facilitates the localization or detection of obstacles and threats, but also their classification [17]. It can capture information such as the position and speed of a submarine, which are crucial for tactical operational and mission management of ASW crews. Processing such information can be very complex as the propagation of sound is a function of many variables such as weather variation, temperature, geographical zone, seasons, salinity, types of underwater landscape and bottom, movements of biological organisms, current and whirlpools, tides and other fluctuating artifacts which might add noise to the signal [18-19].

There are two types of sonars. Active sonars are composed of a receiver (Rx) sonar and a transmitter (Tx) sonar, whereas passive sonars only receive signals to be more discreet and detect/track signals from other sources [17, 19]. In this work, we are interested in the active sonar, for which a chain of pre-processing is applied to enhance the signal and minimize the noise, to then be able to make a decision about the detection [18-19] by:

- Identifying a threat hidden behind noisy signal;
- Being able to measure the parameters of the signal (timing of the propagation, direction); and
- Identifying the characteristics of the threat (recognize the type of vehicles, estimate threat parameters) [16].

### C. Bathycelerimetric Profile

Our use case focuses on the bathycelerimetry profile types, a major feature of the complex underwater environment for sonar, which uses bathycelerimetric data. Bathycelerimetry can be defined as the measure of the celerity for each sound wave based on the distance, depth or pressure, temperature and salinity of the water, but also multiple additional parameters such as bottom type, water density, chemical and biological factors. Therefore, different types of bathycelerimetry profiles are possible based on the zone, temperature, salinity of water and more [19]. For example, temperature decreases as the depth increases. Based on this information we classify the types of bathycelerimetry. The bathycelerimetric profile is a reflection of the depth-dependent temperature and salinity profiles, this enables the calculation of the speed of the acoustic waves. It is also representative of the environmental conditions at the time when the sound emissions are generated (e.g. same place, same season [19-20]).

The acoustic signature can be described as the temporal representation of sound pressure. It integrates all the frequencies generated by a sound source and enables the source to be characterized [20]. This sound helps the sonar operator decide on the type of threat and also helps in the localization of an object or entity. The celerity can be described as propagation speed in meter per seconds (m/s) of a wave-like phenomenon such as an acoustic wave. The velocity of a sound depends on the properties of the medium in which it propagates such as the temperature, salinity and pressure [20]. Within this context, the sonar operator uses two types of outputs from the sonar to make their decision about the acoustic signature, which from their headphone they hear the sound waves emitted by the target entity and received by their sonar Rx. In addition, they are also presented with acoustic images which are the visual representation of the bathycelerimetric information onto a screen.

### D. Current Study

The objective of this study is to demonstrate that DSS could be used to assist sonar operators in deciding on the optimal immersions to place Tx and Rx. Thus, the goal is to enhance operator cognitive performance in detecting threats, by

enabling such systems to have access to similar metrics and information used by the sonar operators. Additionally, this sets a first multi-output models proof-of-concept, which could be integrated in larger ASW technologies and systems such as Smart Assist (see Fig. 1). Smart Assist is a digital assistant aiming at providing a better underwater situational awareness to sonar operators. It is integrated to the operational platform, with no impact on the operational doctrine, and provides live sonar settings recommendations that are reliable, understandable and trustable. Currently in development in the Thales Variable Depth Sonar (VDS) CAPTAS product, it will facilitate automated reporting, allow access to past mission reports, and give relevant recommendations at any decisive moments of the mission across the ASW crew. Real-time recommendations use the current situation and bathycelerimetric parameters, but are also based on AI analytics from an environmental database and large VDS crew knowledge and past experiences.

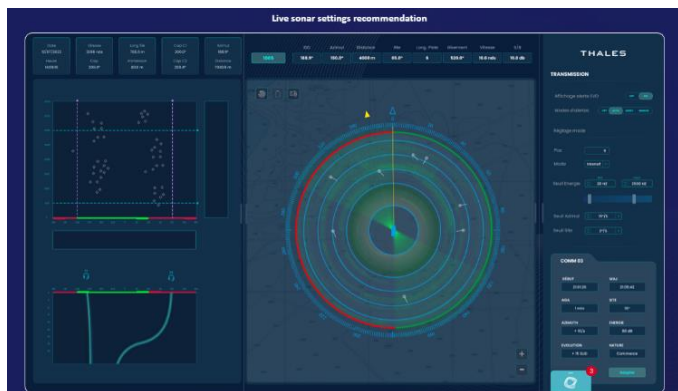


Fig. 1. Smart Assist interface integrated in the Thales variable depth sonar VDS human-machine interface.

### III. METHOD

The work reported here involved two major steps: a) a workshop with domain experts such as Marine Officers and sonar operators in order to understand their challenges, pain points and desire for advancing operational use efficiency of sonar equipment; and b) an empirical policy-capturing data collection, with the development and deployment of our machine learning model for a first proof-of concept study.

#### A. Workshop

A workshop with subject-matter experts from the *Marine Nationale* was held, which included the following participants: commanding officers of underwater anti-submarine warfare operations of the *Marine Nationale* and *Commandant* (Commanding Officer) on the French vessels. We performed human factors interviews and discussions with experts to identify some of the main challenges, priorities and to express their needs for technological equipment and human-machine interaction within their operational context. More specifically, this workshop highlighted the need for support for sonar settings. Through this workshop, the marine experts highlighted some of the challenges including: dealing with a complex environment, fast filtering between false and true alarms, shift

fatigue, complex sonar settings (+300), very long learning and skill improvements, getting and processing large amounts of data, and filtering the information.

This workshop enabled to better understand the environmental challenges and needs to tailor cognitive assistance, by understanding what types of decisions, and the factors which are impacted by the decision. This sets the first step in policy capturing and efficient development research in human-machine interaction for future operational deployment. Indeed, this workshop helped target the essential information needed and required for experts to make decisions, and in return limits the need for data mining and waste in computational process by only extracting relevant features from raw data. Additionally, it also helps reduce the number of examples or sample data to accurately model expert decision making.

#### B. Experiment

1) *Participants*: A total of five experts in ASW from Thales Defence Mission Systems with an average of 17 years of experience took part in the study.

2) *Simulation and data collection*: All five experts were presented with an interface, which simulates a real operational sound wave signal extracted from 20 different cases. Each case varied in sound wave characteristics and sound propagation. Cases varied according to the water depth, geographical zones, temperatures, and bathycelerimetric profile. For each case, participants were asked to write down the optimal immersion values for both Tx sonar and Rx sonar values based on two objectives: a) A detection zone considered as Far; or b) A smaller detection zone considered Medium. Due to the sensitivity of the settings, the ranges cannot be shared. Thus, the simulation would present them with both the imaging of the sound propagation and the acoustic signature.

Based on those two pieces of information, the sonar experts needed to make the decision on which immersion value pair (Tx-Rx) would maximize chances of detection of a submarine. Based on the subjective nature of this decision (there is no known objective measure of right and wrong, that is, no available ground truth), the experts were given the possibility to capture more than one answer (up to three) from the most to least optimal option. This is important, as there are up to 300+ possible settings and often experts do not end up with the same decision due to their different reasoning and decision-making pathways. The total amount of data collected can be presented as 20 cases  $\times$  5 experts, leading to 200 labelled cases with additional decisions in second and third top choices (for a total of 255 cases).

3) *Machine learning pipeline*: The machine learning method implemented relied on multi-output supervised models for regression (i.e., where the outputs are continuous variables) using the Scikit-Learn Python library. Multi-output models enable the DSS to predict decisions, which are composed of two interdependent parameters, which are Tx and Rx. The machine-learning pipeline is composed of several steps following the experimental design and the data collection, described in Fig. 2.

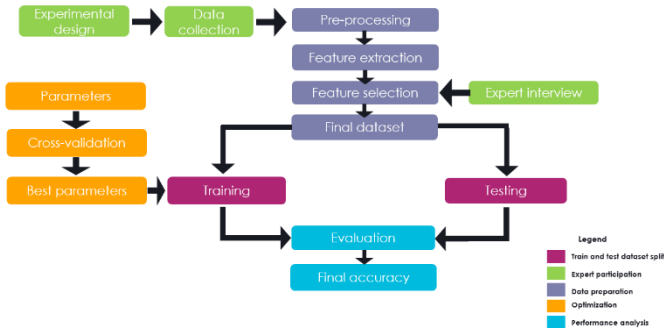


Fig. 2. Machine learning pipeline composed of data preparation (dark blue), modelling and testing (purple), optimization (orange), performance analysis (light blue), expert participation (green).

Once the data is acquired, our machine learning pipeline involves the following stages:

- *Pre-processing*: This stage consists in cleaning the data, and sonar signal as well as making sure our labels Tx and Rx are well distributed to avoid future bias;
- *Feature extraction*: Extracting higher-level information from the data such as bathy type or the most significant features from the dataset;
- *Feature engineering*: Transforming the data into easier processing format and normalize the data through methods such as one-hot encoding;
- *Feature selection*: Based on the most important factors considered by the experts, we select the appropriate features to be implemented into the model;
- *Modelling and training*: The four models used are Decision-tree, Linear-Regression, Random-Forest and K-Nearest Neighbor;
- *Optimization*: Once this is achieved, the dataset is split between training (with hyperparameter optimization) and testing, using a final 10-fold cross-validation to assess predictive accuracy on the held-out data.

a) *Preprocessing and feature extraction*: Preprocessing involves making sure the dataset is balanced and well distributed to avoid bias in Tx and Rx prediction. After collecting the data and running a preliminary analysis, some feature imbalances were detected (e.g. the geographical area did not sample the broad variability possible). For example, the majority of cases fell in one or two geographical areas. This might create some biases in the predictions of the model, and how the model trains and learns. Therefore, we applied a data augmentation strategy using plausible synthetic cases to diversify the database and reduce risks of bias. Data augmentation enabled to add cases with feature variants that were assumed not to impact decision outcomes. Secondly, this phase involved extracting the features, which are affecting both the acoustic signature as well as the sound waves imaging, perceived by the expert to make its decision. Features extraction can be represented in Table 1.

TABLE I. FEATURES EXTRACTION

Features	Definition	Ranges
Bathy Type	Represents the classification of the curve based on its celerity profile.	[0-5]
Temperature (Celsius)	The seven layers of depth-dependent temperatures, represented by 7 variables (e.g., Temperature1, Temperature2, ...)	[25, -2]
Goal	Binary classification based on the distance ranges for detection: Medium or Far.	[0-1]
Velocity (ms)	The seven layers of depth dependent velocity (velocity at depth1, depth2, ... depth7)	[1400-1550]
Geographical Zone	Geographical zone based on the type of sea or ocean.	[0-3]
Depth (m)	Represents the 7 layers of deep-water depth immersions.	[0-6000]

Note. Velocity values were rounded for sensitivity reasons.

b) *Feature engineering and selection*: Feature engineering was needed to transform some of the features extracted into the proper format using methods of encoding using sklearn.preprocessing LabelEncoder. Secondly, we only selected the most relevant features and dismissed the ones the experts did not take into consideration when making their decisions. This was conducted via a small interview (cf. Fig. 2).

Lastly, the selection process was enhanced using a deconflicting algorithm (Fig. 3). This algorithm was a necessary step to help in dealing with incompatible decisions across experts. This enabled the model to avoid having conflicting labels for the same case. We created a deconflicting function, which enabled us to converge toward a best choice based on two strategies (Fig. 4).

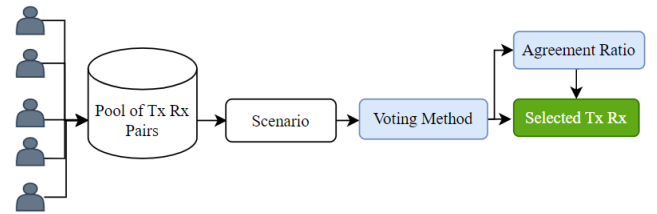


Fig. 3. Deconflicting pipeline.

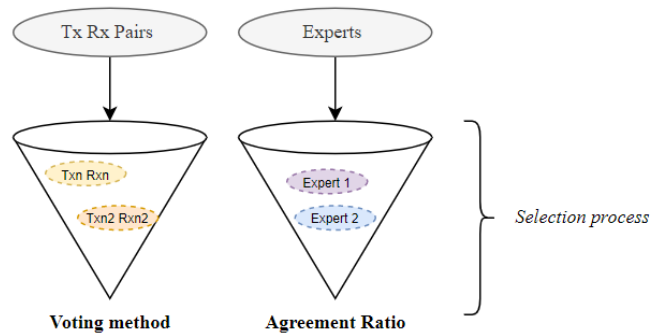


Fig. 4. Methods of de-conflicting: Voting method and Agreement ratio (from left to right).

The first one is by voting for the pair (Tx, Rx) with the most common agreement among all experts. The second strategy is based on an agreement ratio, which could be seen as a clustering on the average of responses of each expert. This means that if the algorithm has often selected an answer from one or two experts, which themselves means they agree with most other decisions, the algorithm will interpolate and decide on picking the answer of the expert the majority agreed upon. If no majority answer emerged, then the algorithm would select one based on the agreement ratio method.

*c) Modeling and optimization process:* The dataset is split between training and testing. The model training process includes hyperparameter selection through cross-validation following grid search, as well as cross-validation of the model accuracy. The model evaluation uses the 10-fold cross-validation process, sharing the dataset into 10 folds, at each iteration comprising 90% of the training data and 10% of test data. Lastly, the validation scores are used as the final model’s performance, which are compared differently depending on the aggregation method selected. Therefore, the accuracy results from 10-fold cross validation and trained hyperparameters. Each set of hyperparameters from the machine-learning algorithms is also trained and cross-validated using a 10-fold rule. The best ensemble of hyperparameters used and last cross-validation are performed to determine the final accuracy. Lastly, to select the models, we used the “Best Aggregation” which defines the recommendation of Tx and Rx according to the model which is better at predicting all the different possible Tx-Rx pairs, using the average of their predictive accuracy. Examples of such methods have been also deployed and proved efficient using Cognitive Shadow [22]. This aggregation method helps select which of the four algorithms is then selected for recommendation.

### C. Data Analysis

1) *Expert homogeneity analysis:* The expert homogeneity analysis enabled us to assess the degree of agreement over the decision across all five experts for each use case. In order to analyze the differences and variation in decision making across experts, we have developed an Expert Homogeneity Analysis metrics which is classified between three classes:

- *Low:* If all Tx-Rx pairs are different for all experts, and the selection process picked the one based on an agreement ratio.
- *Medium:* If there is a tie in voting methods between two Tx-Rx pairs, however the best agreement ratio expert is not within those two options.
- *High:* If most of the expert agreed on the same Tx-Rx pairs using the voting methods or if there is a majority for two Tx-Rx pairs and the best agreement ratio expert is within one of them.

Based on Table 2, we can observe a higher consensus over the goal with a Medium range than with Far. Global represents when the analysis was made regardless of the goal, which demonstrates that overall, there is still very high variation

between experts in predicting and deciding the best Tx-Rx immersion parameters.

TABLE II. EXPERT HOMOGENEITY ANALYSIS

Goal	Low	High	Homogeneity %
Medium	6	14	70%
Far	8	12	60%
Global	14	26	65%

We observe overall a greater proportion of high cases of homogeneity, with a reduced homogeneity for the Far detection objective. However, we still note that the variation between both classes is only represented by a difference of 10%. The formula for the percentage of homogeneity can be calculated as shown in Equation (1) for each goal:

$$Homogeneity \% = \frac{High \times 100}{High + Medium + Low} \quad (1)$$

We observed no case where the expert was not part of the tied most-voted Tx-Rx pairs. This homogeneity metric is important as it helps demonstrate conflicting reasoning across experts. However, due to reasons of confidentiality, we are unable to share the statistical results of the variation of Tx-Rx pairs across experts on the different cases assessed.

2) *Patterns and tendencies in features:* Major patterns have been detected through the analysis of individual features. The first and major marker of the variability in feature is founded on the depth. As Fig. 5 demonstrates, the deeper the water, the higher variability and higher standard deviation are found across all uses cases. As for temperature, the deeper the water, the less variability is observed. Lastly, velocity does not demonstrate this correlation pattern. However, we note higher velocity within deeper water (i.e. for depth 7). This analysis enables determining how different components of the batycelemetric profile might affect model performance.

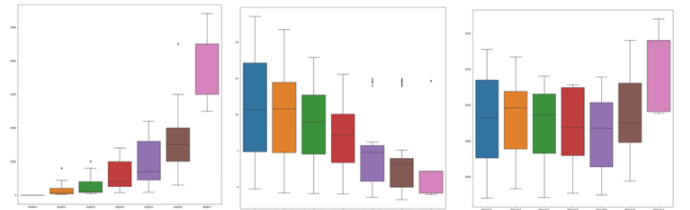


Fig. 5. Feature variability based on: i) Depth (1-7); ii) Temperature (1-7); and iii) Velocity (1-7), from left to right.

3) *Models testing:* In order to assess the performance of the different multi-output models, we considered two accuracy metrics on the validation data,  $R^2$  (indicating the proportion of variance accounted for by the model) and the Root Mean Squared Error (RMSE), which represents the average absolute error (deviation) of the predictions.

## IV. RESULTS

We compared the test accuracy between the four different models based on the goal (Far, Medium or Both combined). First, the results demonstrated a higher accuracy in predicting

Medium with 96.46% and closer range immersion metrics than Far with 85.89%. This is also aligned with the expert homogeneity analysis, where we detect higher consensus over closer ranges than for far ranges. For Medium ranges, the highest accuracy was achieved with the decision-tree model with an accuracy on validation data with 96.46% with an RMSE on validation of 4.74 meters. The second-best model was KNN with accuracy on test data of 90.63% with an RMSE on validation data of 11.79 meters.

For the Far detection goal, the highest performing model was a decision tree with 85.91% with an RMSE validity of 9.99 meters, closely followed by the KNN model with an  $R^2$  of 85.89% and an RMSE of 13.80 meters. The second-best performance is attained by the random forest with an  $R^2$  accuracy of 76.64% and an RMSE of 22.83 meters. Lastly, we can observe a poor performance for the Global models (combining Medium and Far cases), suggesting that attempting to simultaneously capture heterogeneous decision patterns in a single model can be counterproductive and may lead to poor generalization. Nonetheless, the KNN model succeeded in achieving a high global predictive accuracy of 99.94% with an RMSE of 1.22 meters. We observe a general higher predictability in Medium and Far over Global. There are higher discrepancies across models within Global compared to Medium and High, which would need further investigation. In addition, we would like to highlight that limited analyses were presented herein due to the sensitivity of the data.

TABLE III. MODEL PERFORMANCE

Goals	Multi-Output Regression Models Accuracy <sup>a</sup>			
	Linear Regression	Decision -Tree	Random Forest	K-Nearest Neighbour
Medium	85.37%	96.46%	83.16%	90.24%
Far	73.72%	85.91%	76.64%	85.89%
Global	29.99%	71.31%	43.57%	99.94%

<sup>a</sup> Accuracy reflects the  $R^2$  (in %) for the multi-output supervised machine learning regression algorithm.

## V. DISCUSSION

The policy-capturing study reported herein aimed at demonstrating that experts' decision making for sonar parameter management can be accurately modelled using multi-output regression models. A group-of-experts model derived using this method can in turn be integrated as part of a real-time DSS system recommending Tx and Rx pairs to the user, yet keeping the human expert in the loop and in charge of decision making. Results demonstrate that despite the relatively small dataset, high accuracy (above a typical acceptability threshold of 80%) could be achieved using this policy-capturing method designed for learning with sparse data. While these results provide a compelling proof of concept for the feasibility of this approach, more work is needed in order to have a fully deployable mission-ready solutions.

Several future improvements are already under consideration. One first potential improvement would be to ensure a more diverse set of cases to ensure good sampling

coverage of the parameter space, which is essential for good generalization in operations. A second potential improvement concerns our deconflicting methods which could be enhanced by taking into consideration years of experience, time in missions, or specifics about the experts' operational experience (e.g., mainly in one geographical area, or with one type of sonar). This first proof-of-concept study enables us to dive-in further within such methods and help target and optimize the next experimental design and data collection to produce a higher-maturity model. Additional parameters and features could be added in order for the machine-learning models to better understand the range of factors, as in other work such as [23].

Future work will also need to examine how to best provide explanations about recommendations to end users, in part to improve technology adoption but also to allow the human expert to review recommendations and decide to either accept or override them (which in turn can lead to further model improvement). Trust is a major feature for proposed digital AI-based techniques into operational doctrines.

Explainability features are also implemented within Cognitive Shadow, through the use of SHapley Additive exPlanations or also called SHAP, which helps determine the weights of each feature or the coefficient of each feature for the prediction [24-25]. Yet, this component was not tested as part of the current study and, therefore, the experts could not receive any feedback from a DSS, nor any information with respect to the model's explainability. SHAP values could help improve transparency towards the types of recommendation and Tx-Rx predictions made by the system, a component that should be addressed in the future.

The intended practical application of this work is to insert such a learning and decision support module within the Smart Assist solution having a broader set of skills designed to bring a disruptive cognitive advantage to the ASW crew. The solution especially focuses on quickening the decision cycle of the sonar operator, sonar coordinator and underwater warfare officer roles and providing a security net to sustain nominal performance in adverse conditions. Expected operational benefits of the resulting decision-support capability are reduced mental load, improved situational awareness and enhanced decision speed/accuracy, leading to improved mission effectiveness and survivability for ASW, although DSS/automation integration must be carried out with caution [26-27].

Interestingly, the operational deployment of such a capability will also enable further data collection and allow iterative refinements and continuous adaption to the evolving operational environment. Given these possible outcomes, future work will also encompass the evaluation of mental workload, situation awareness and decision performance, compared with group-of-experts majority ground-truth responses, in order to test the operational benefits that such a DSS based on the principle of policy capturing could actually bring to the sonar experts.

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