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Review

# Developing AI enabled sensors and decision support for military operators in the field

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ABSTRACT

Wearable sensors enable down range data collection of physiological and cognitive performance of the warfighter. However, autonomous teams may find the sensor data impractical to interpret and hence influence real-time decisions without the support of subject matter experts. Decision support tools can reduce the burden of interpreting physiological data in the field and incorporate a systems perspective where noisy field data can contain useful additional signals. We present a methodology of how artificial intelligence can be used for modeling human performance with decision-making to achieve actionable decision support. We provide a framework for systems design and advancing from the laboratory to real world environments. The result is a validated measure of down-range human performance with a low burden of operation.


## Practical implications

- Raw data from wearable sensors and remote physiological monitoring is not actionable in an operational setting.
- The burden of monitoring sensors can be reduced with AI models.
- Decision support systems can increase the knowledge, skills and abilities of operators in the field.
- Autonomy can be increased when using decision support tools for human-machine teaming.

## 1. Decision-support system

In safety-critical professions (e.g., warfare, aerospace, firefighting, piloting, space travel, air traffic control, and sports) individuals must make rapid tactical decisions based on many data sources. Real time monitoring of an individual's physiological and cognitive status can potentially aid the speed and accuracy of tactical decisions. Recent developments have combined sensors with artificial intelligence (AI) to deliver precision medicine with individualized metrics of health and performance.

Remote Physiological Status Monitoring (RT-PSM) systems use sensors to measure and calculate health and performance of an individual by utilizing wearable sensors and ambient detection. This real-time monitoring of an individual's physiological and cognitive status can potentially aid in tactical decisions down range. For example, heart rate monitors allow estimation of an operator's physical performance and energy systems during exercise/exertion. However, heart rate alone does not facilitate an actionable RT-PSM system due to secondary effects such as: physical load; body position (e.g., laying vs standing); recovery from recent exercise; sleep status; emotional state (e.g., relaxed vs afraid); dehydration; digestion of food/ingestion of ergogenic aids (e.g., caffeine); core temperature (e.g., vasodilation from temperature or blood loss) and possible viral infection.

The challenge of interpreting human performance data from a RT-PSM system can be solved by incorporating it into a decision support system (DSS). A DSS combines sensor data with artificial intelligence (AI) models to deliver problem solving, actionable choices and observation.[1] This article proposes a framework to determine the development of an AI assisted DSS including RT-PSM and reviews common goals of DSS, including that the system should:

- Be low burden to for operator time, cognitive load and physical distractions[2]
- Be low size, weight and power (SWaP)
- Be context aware of the current situation
- Augment the operators' knowledge, skills and abilities (KSA)[3]
- Be based on an appropriate underlying hierarchy of models
- Share information from a database of decision-relevant information

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- Provide information that aligns with the decision-maker's expectations and mental model[4]
- Support judgments rather than replace them
- Operate at a high level of trust.[5]

## 2. Evolution of decision-making models toward a systems perspective

Decision-making is a problem-solving activity that yields a solution. Several Naturalistic Decision Making (NDM) models have been developed,[6] one of which is referred to as the Recognition-Primed Decision Model (RPM).[7] Briefly, the RPM hypothesizes that people use their prior experiences to build a repertoire of patterns, including training, not just real-world experiences. These patterns include relevant cues and suggest typical types of reactions for that type of situation. If a commander, for example, needs to make a decision, they quickly match the situation to learned patterns and visualize how that same course of action will play out in the current context. When there is a clear match and the mental simulation suggests that a previously used solution would work in the current context, the commander will carry out that action. Therefore, decision-making in-the-field is a blend of intuition and analysis.

In 1995, John Boyd[8] first presented the now well-recognized OODA loop of human decision making (Fig. 1). The OODA loop concept describes decision-making as a cycle between observations, orienting, deciding and acting. Basically, as a situation evolves the decision-maker observes, with attention primarily focused on the current problem. Orientation focuses observations based on prior experience and knowledge drives the focus. It is here that the observations are processed. Decisions and actions are based on the current information and knowledge of possible choices. The tempo of the OODA cycle is critical in situations where the goal is to out-think an opponent (e.g., during a battle, on a football field, medicine-where the opponent is the illness or disease).

Other recent research and theoretical endeavors have focused on human "anomaly resolution" by individuals and groups. For example, Woods[9] defined an iterative process composed of recognition, troubleshooting, response, and contingency management. To resolve an anomaly, it must first be detected. This involves recognizing anomalous data or an anomalous situation. The source of the anomaly must then be diagnosed through troubleshooting. This is where prior experience or training has established expectations that focus attention to what is relevant. The initial interpretation and response affects how the anomaly will progress.

In the next section we discuss the application of artificial intelligence (AI), as a systems-based computational tool that can learn the complex relationships between system inputs and outputs without explicit programming.[22]

## 3. Artificial intelligence

A model in the context of computer science refers to software code that performs a function. AI models can achieve human level accuracy performing certain cognitive tasks. These models range from simple classification models (e.g., cats vs dogs), regression models calculating continuous variables (e.g., human activity recognition from acceleration or heart rate from plethysmograph waveforms) to more complex computations including probabilistic decision making. Broadly, AI models are split into supervised or unsupervised learning algorithms. Supervised AI models require labeled data to learn patterns that differentiate categories (e.g. cat vs dog). Unsupervised models determine correlations which assist with labeling and dissemination in decision making systems.[10]

Deep learning is a subset of AI that automatically learns complex relationships between high dimensional inputs to determine the most important features related to the outputs of interest.[11,12] Deep learning models are commonly described as opaque, or "black box" models as they offer a high degree of predictive accuracy at the expense of explainability of the underlying relationships between inputs and outputs. Trust is important when using predictive models and typically involves explainability and validation results. Table 1 provides a subset of computational models ordered by explainability. AI and decision support tools requiring trust have been used successfully in fields such as bioinformatics[13,14] and neuroradiology.[15,16]

In the subsequent sections of this discussion, we describe a framework of how AI/deep learning can aid in the exploration and development of a DSS.

## 4. Finding the signal in environmental complexity with AI

A systems theory perspective assumes the whole is greater than the sum of its parts. Ahn[17] described the systems perspective succinctly by stating "the systems perspective is rooted in the assumption that the forest cannot be explained by studying the trees individually". A defining feature of the systems perspective is how environmental factors that introduce variability within the system are viewed. Rather than viewing this variability as nuisance noise to be methodologically

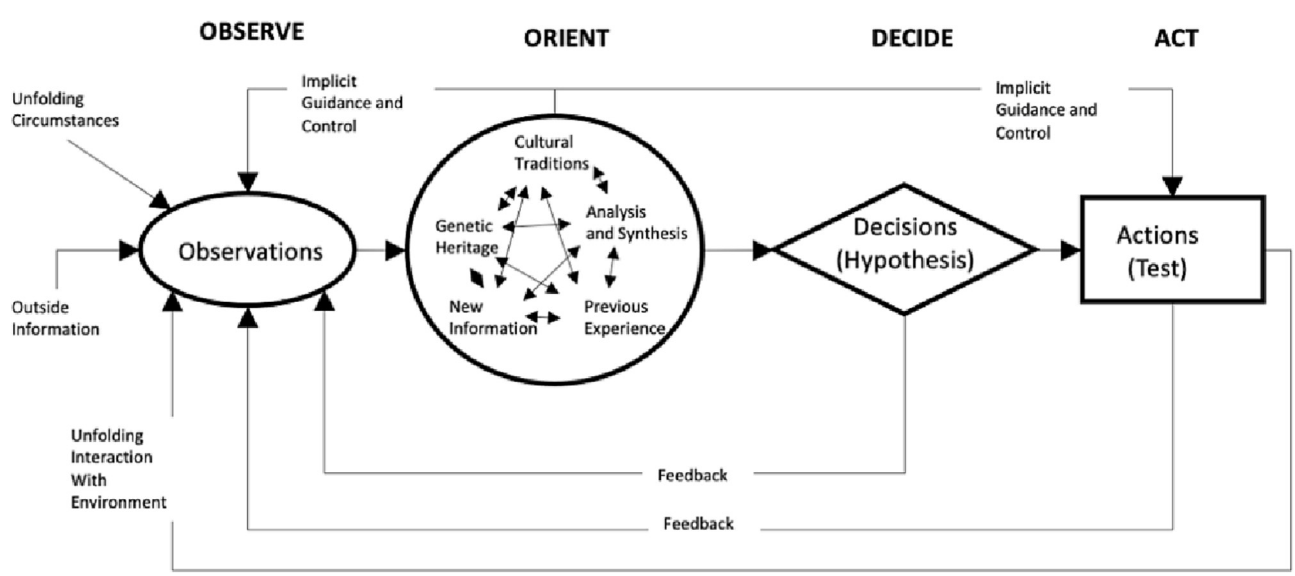


**Fig. 1.** Boyd's OODA loop, a cognitive model for decision making.

**Table 1**
Explainability listed by examples of computational approaches.

| Explainability | Type of model | Example type | Example application |
|---|---|---|---|
| Highly transparent | Linear algebra | linear model | Modeling muscle respiration[40] |
| | Calculus | Differential equation | Skin surface temperature modeling[41] |
| | Statistics | ANOVA | Effectiveness of different treatments[42] |
| | Fuzzy logic | Fuzzy model | Diagnosis of cardiac hypertrophy[43] |
| | Bayesian models | Conditional probability | Diagnosis of medical condition[44] |
| | Tree based | Random Forest | Prediction of energy expenditure[45] |
| | Component Analysis | Principal Component Analysis | Facial recognition[4] |
| | Feature-based machine learning | Support Vector Machine | Predicting Ion exposure form cognitive performance[46] |
| | Artificial intelligence | Convolutional Neural Network | Classification of human activity[19] regression analysis of ground reaction forces[47] |
| Highly opaque | Artificial intelligence | Recurrent Neural Network | Prediction of cognitive load from speech[48] |

controlled or removed, a systems perspective views this “noise” as a crucial component required to predict behavior within the system. Traditional laboratory assessment protocols require an intervention with a measurable outcome (e.g., jump height or Stroop Effect). Commonly, field studies will utilize a battery of tests and determine which were sensitive to the protocol load after completing the protocol. However, these interactive tests are not practical for operators in the field as they are distracting and require cognitive and physical interaction. Alternatively, ambient detection observes an individual's performance at a task to compute an output value, e.g., the timing from keyboard use can be combined with an AI model to determine cognitive fatigue.[18] A decision support tool can integrate this information to reduce interaction and only require cognitive burden when guiding attention to an anomaly and assisting with decision support.

Consider the example waveforms presented in Fig. 2, from Russell,[19] illustrating an acceleration waveform of a person running outdoors down an incline on a smooth sealed road versus a dirt track. The shape and silhouettes of each waveform demonstrate that running on a dirt track introduces more complex gait mechanics compared to a smooth surface. Russell[19] showed these waveforms could be used by an AI model to detect signals such as surface type, slope, activity type and fatigue.[20] The environmental signal was noise for activity recognition but the signal of interest when detecting surface type.

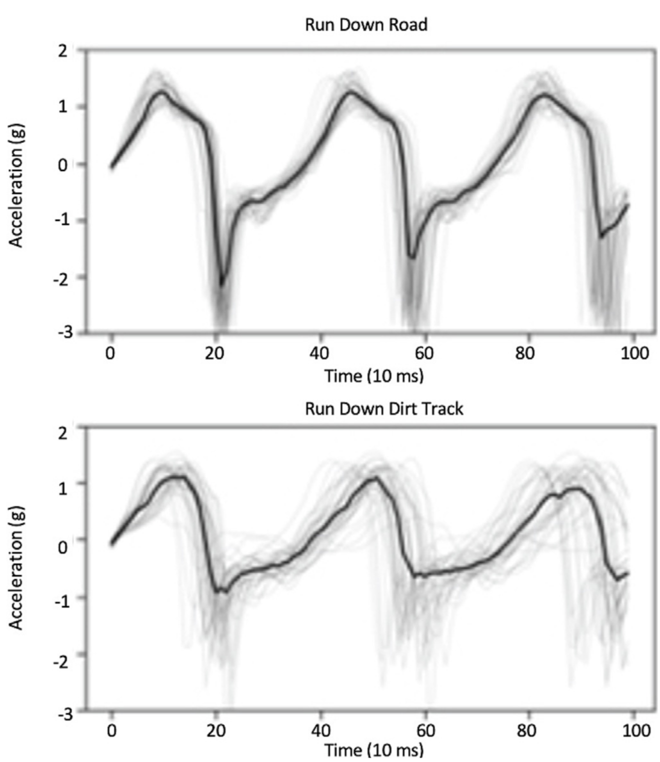


**Fig. 2.** IMU waveforms for running down slopes of various terrain types (sealed road vs dirt track),[19]

## 5. A hierarchical system of models

Implementation of decision support typically involves multiple AI models. Crump[21] discusses an AI stack for implementation of an ethical medical decision support system based on the ISO 7 layer stack used in communications engineering. A decision support system is implemented in an hierarchical architecture, such as the OODA loop, with computed information being passed up and feedback loops generating new data for lower stages. Each stage of the decision making process can be considered as a hierarchy of opportunity for computational tools to assist the human operator. Observation is automated through sensor data collection including ambient detection[22] to reduce the need for additional activities. AI models can assist with orientation by interpreting data, often better than a human, by tirelessly observing time series data such as accelerometery and determining higher order features such as fatigue. The decision state is typically modeled with a Bayesian approach to probabilistically determine which information is required to differentiate between decisions using the highest positive predictive value. Actions are chosen by an expert systems model (Fig. 3).

The following section provides practitioners with a systematic methodology for identifying valid, non-invasive performance measures for the prediction of real-world task performance decline so that useful countermeasures, such as decision support or information integration, may be proactively provided.

## 6. Selection of valid performance measures

### 6.1. Measure dependencies

An individual's ability to perform in a range of safety-critical tasks can be fatigued by stressors which negatively affect physical and cognitive abilities. Stressors shown to affect performance include exposure to hot or cold temperatures,[23] pain,[24] physical inactivity,[25] isolation,[26] time pressure,[27] concussion,[28] high workload[29] and sleep deficits, to name a few.

The physical or cognitive ability affected (e.g., visuo-motor responses, sustained attention, selective attention, higher level problem-solving) depends on the stressor type, duration, and intensity. As examples, time pressure can result in overlooked critical information,[30] concussions have an association with reduced mental flexibility,[31] and sleep deprivation has been shown to affect concentration.[32] To further complicate matters, each individual reacts differently to stressors.[33,34]

Many studies have explored methods for detecting, monitoring, and aiding performance. However, poor transferability of these

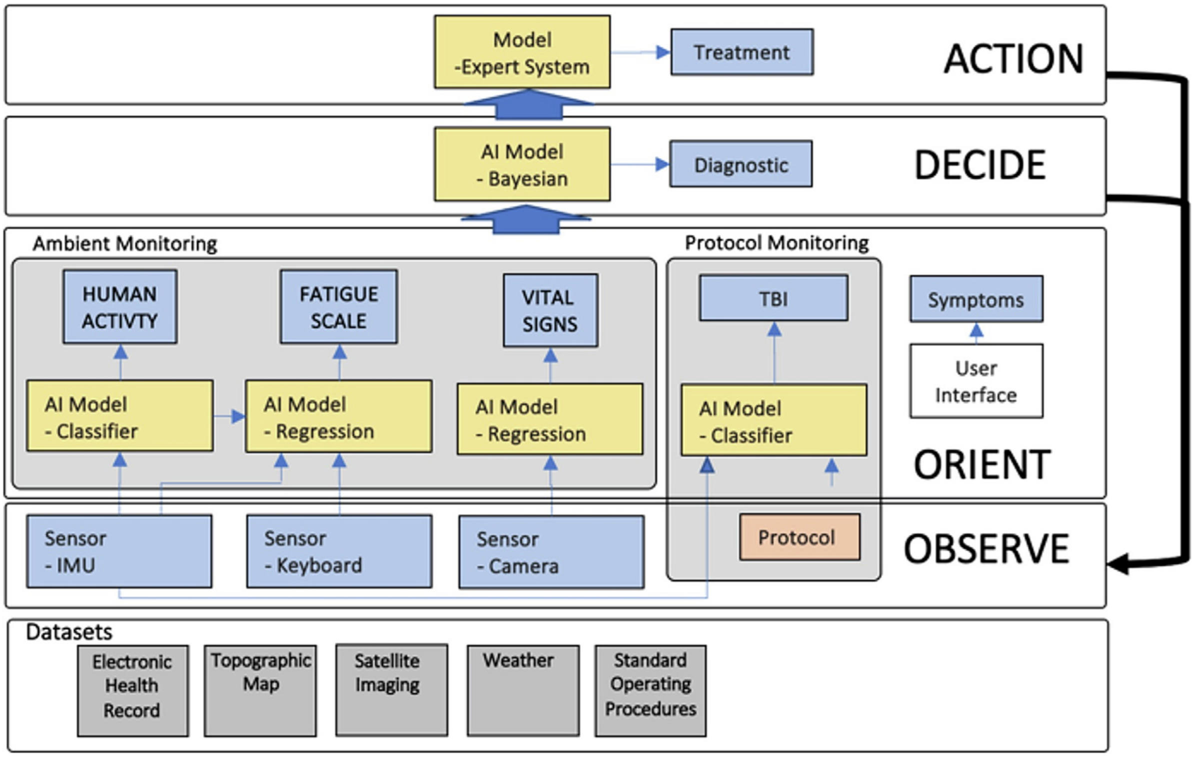


**Fig. 3.** Hierarchy of computational models to the OODA decision making loop.

methods from simulation to the field suggests that either different cognitive processes are being assessed or that the complexity of operations have not been captured. In many cases, technology selection is based on cost, availability, or successful application in another domain. Little attention is given to determining how changes in activity or sensor profiles compare to the individual's (or group's) tasks at hand, what cognitive or motor abilities are needed to accomplish those tasks, the stressors currently being experienced, or how performance or those tasks are affected by the individual or combined stressors.

### *6.2. Define safety-critical tasks*

Each position in a profession has specific roles and responsibilities. Task analysis, performed by a trained human factors specialist, identifies the tasks that must be supported for a particular position. If tasks include safety-critical mental effort or critical decisions, then a cognitive task analysis (CTA) should be performed. CTA uncovers what the individual needs to know (e.g., information needs) and strategies used to think through the decision. In addition to helping define a sensible performance metric, CTA is invaluable for training development, interface design and procedure development.

Once a complete CTA has been performed, pinpoint those tasks that are performed during safety-critical operations. For example, a TRACON arrival air traffic controller must often integrate visual information from a variety of displays (e.g., arrival rates, aircraft speeds, wind, the time, projected arrivals). Therefore, visual information integration is a candidate ability to monitor for performance decline and/or for which to develop technological support.

### *6.3. Define stressors*

The specific stressors the population will be exposed to prior to and during the time-frame of the critical decisions should also be determined. Imagine an astronaut on the International Space Station (ISS) who is piloting a robotic arm located on the outside of the ISS. The astronaut is being exposed to microgravity, a high workload, possible vision changes, elevated $CO_2$ in the cabin atmosphere, an audience of millions, etc. All stressors should be identified.

### *6.4. Align stressors with critical tasks*

Next, determine how performance has been compromised with exposure to each stressor alone, and in concert.[35] This alignment is based on the published, scientific literature. For example, elevated $CO_2$ has been shown to affect visuo-motor abilities needed to adjust the robotic arm position.[36] Therefore, sensors indicating elevated $CO_2$ could communicate with technology that adaptively provides additional visuo-motor guidance. As another example, imagine a scenario where a single fighter pilot must navigate to a specific target in a well-hidden location to eliminate a threat. To find the location may take several hours at which time he will be running low on fuel, and he is not equipped with a water canteen. Both time–pressure and dehydration have been shown to affect spatial navigation, even in expert pilots.[37] Whenever possible, the correlation between the field stressors and the specific real-world task identified should be validated.

In summary, knowledge of specific safety-critical tasks and known stressors that affect performance on that task can help define a pragmatic performance metric. It is likely that a combination of measures will be needed. Additionally, knowledge about potential degraded performance can be used a priori to make design decisions and to determine effective countermeasures.

## 7. AI research and development framework

A challenge when developing AI models with wearable sensor data is how to efficiently and effectively handle the sheer volume of data that these sensors provide. The researcher and developer have choices on what sensor types to use, how frequently data should be sampled, stored, transmitted, or analyzed. Often the raw sensor data is too

**Table 2**
Research protocol for AI enabled models.

| Stage | Decision or task | Description |
|---|---|---|
| 1 | Determine mission outputs | Outputs required to be valuable to the operator and the mission. Establish how these requirements will be quantified. |
| 2 | Select Clinical Assessment Battery | Used for AI model training and validation |
| 3 | Determine field protocol for data collection | Representative data for different scenarios, sufficient collection of assessment battery to enable high resolution of AI training |
| 4 | Data Collection Tools | To be used by research staff on field, that may be fatigued and distracted with intermittent power, data logging and communications |
| 5 | Label Data | Add labels to data to enable AI model to learn |
| 6 | Protocol study | Perform prototype study on low subject numbers to prove functionality of the protocol, tools and computational models. |
| 7 | Large study | Perform field trial to validate the research. |
| 8 | Deploy | Deploy fieldable tool |

verbose for system limitations including battery power, storage capacity or communication bandwidth. The trade-offs require local analysis to deliver higher level information for onward transmission, e.g., a plethysmograph (PPG) 100 Hz 2 channel signal from a wrist device is used to calculate and store blood oxygen ($SpO_2$) versus heart rate at 1 Hz.

Validation of opaque AI models requires black box testing under many representative scenarios to guarantee performance in unconstrained environments. With AI development these data are required at the beginning of the research to train the model and also at the end of the project to validate performance. AI enabled human performance monitoring requires a method to gather data in the field to both train the AI model and validate its performance. This 'black box' approach differs from reductionist science in that it asks the question:

> "Can an AI model accurately predict outputs with a given dataset and, if so, what data is required to find the signal?"

A process is required to develop an AI model including input data representing real world use cases, outputs valuable for intended use, and comparison gold standards to both train the model and validate performance. Field considerations for the team collecting data in remote environments should take into account: spare parts due to lack of resupply, fatigued and distracted research assistants, safety, environmental noise (e.g., weather, terrain including slope and surface types, obstacles, non-uniform inclines and surfaces), operational noise (e.g., fatigue, sleep deprivation, operational distractions such as contact with the enemy or wild life) and performance selection such as self-pacing and activity type (e.g., walking, running or laying during rest periods), sensors to represent fieldable solution options (SWaP), additional sensors needed for logistics, and protocols to generate required loads (physiological, centraland psychological).[20,38–40]

This method is recommended with low subject numbers initially, N, as the logistics of field experiments is complicated and data analysis and processing is time consuming. Pilot experiments will inform the protocol and validating AI models with small N numbers allows the approach to be proven. It is recommended that generalizability to larger populations is considered an important second step. Of particular note is Step 5 in Table 2 as this is unique to AI modeling where data are labeled with additional information to enable the training step where the AI model learns iteratively by measuring its predictive accuracy against the labels.

## 8. Conclusion

Remote physiological monitoring can be useful when incorporated into a DSS enabled with a system of AI models. This approach enables a lower number of sensors, with lower SWaP, as ambient sensing can use operational tasks as a stimulus to replace protocols. AI can use environmental noise as signal and expert decision making can bring complex probabilistic decision-making down range increasing the knowledge skills and abilities of operators.

Adapting to field conditions has challenges that, if overcome, promise to increase performance, without adding additional burden to remote autonomous operators down range. Field noise is both a challenge and a stimulus for the ambient detection of response to the stimulus when assessing performance or other parameters. Data collection for research with AI modeling requires special field protocols. This systems approach offers the promise of decision support tools aiding the warfighter operating autonomously down range in the near future.

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