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Human Digital Twin and Modeling Guidebook

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1.0 Preface

Model Based Systems Engineering is rapidly being adopted to aid the design and early evaluation of engineered systems (Delligatti, 2013; Friedenthal et al., 2014). More importantly, these tools are quickly being adopted by the United States Department of Defense and their contractors with the goal of increasing the rate of product acquisition and reducing system sustainment costs (Roper, 2020).

Unfortunately, the operators and personnel in these systems are usually considered external actors in the system models who interact with the system during its operation (M. Watson et al., 2017). As a result, the supporting models are unlikely to represent the total performance of the system when the system is operated by representative personnel. Additionally, Air Force personnel with experience in evaluating and modeling human performance rarely have the expertise to adequately represent the human within these models. Further, standards and guidelines do not exist for modeling humans as part of these system models.

The existent system models, while being useful to aid the design, specification, and acquisition of systems, have value in other phases of the system lifecycle. Additional research is illustrating the use of these models during system operations and sustainment. Within these phases of the system lifecycle, these models may be embedded within digital twins to aid the improvement of Tactics, Techniques and Procedures (TTPs). Improvements in TTPs improve overall performance of fielded systems and the operators within these systems.

Within this report, we begin by exploring the definition of Digital Twin technology to aid the definition of Human Digital Twins. We further explore the literature on the application of human modeling in MBSE models as they relate to system acquisition, focusing on metrics which are important in acquisition. Through this lens we propose a potential vision for the application of Human Modeling to support the product lifecycle while providing some insight into the use of these models for aiding understanding of the human (airman) in the system lifecycle. Finally, we begin to explore frameworks for human digital models and discuss some of the underlying issues and barriers to the development of integrated human digital models within both system models and human digital twins.

1 Defining Human Digital Twins

1.1 Defining Digital Twins

An outcome of the industrial revolution and mass production is the standardization of products. This process has many advantages, including the ability to create many product copies from a single design and the ability to leverage scale to reduce overall product cost. Another advantage is the ability to use standardized parts during system operation and sustainment to reduce the cost of maintenance. While the variability between products is controlled during manufacturing, their use often varies, increasing the differences between products. If these differences are not accounted for, the variability decreases the ability to properly estimate product performance and plan maintenance cycles. Further, specific products within a product family can be designed and built with slight differences to enable specific mission sets, placing further stress on logistics for sustainment of these products. Digital twin technology has been developed in recent years to address the problems which arise from product and environmental differences (Tuegel et al., 2011). The digital twin concept includes constructing a digital representation or model of an individual product to improve the accuracy of maintenance and performance predictions for individual products (Kobryn, 2020). Thus, a digital twin has been described as the model of a component, product or system developed by a collection of engineering, operational, and behavioral data which support executable models, where the models evolve over the lifecycle of the system and support the derivation of solutions which assist the real time optimization of the system or service (Boschert & Rosen, 2016).

Recently, this term has been extended to humans using the term "human digital twin". This term has been applied in diverse fields, including medicine (Chakshu et al., 2019; Corral-Acero et al., 2020; Hirschvogel et al., 2019; Y. Liu et al., 2019; Lutze, 2020), sports performance (Barricelli et al., 2020), manufacturing ergonomics (Caputo et al., 2019; Greco et al., 2020; Sharotry et al., 2020), and product design (Constantinescu et al., 2019; Demirel et al., 2021). Although the human digital twin concept may be analogous to digital twins of products, there are distinct differences, including increased underlying variability between humans and the fact that humans often employ products to achieve their goals. Commonalities can be observed in the use of the human digital twin concept across the fields where it has been applied. For example, each of these fields discuss constructing and applying a model of humans which is informed by data collected from sensors that provide insight to human behavior and performance in real world settings. However, there are also differences. For example, in medicine or sports performance, the models often focus on improving the human or human performance while in manufacturing and product design, the model's focus is on improving either the process or the artifacts with which the human interacts. As a result, the components which are modeled within each of these applications differ.

The Merriam-Webster Dictionary defines the noun twin as 1) either of two offspring produced in the same pregnancy or 2) one of two persons or things closely related to or resembling each other. These two definitions refer to both a temporal relationship between the creation of the two entities as well as the ability of one of the entities to represent the other entity, either physically or behaviorally. As we will see, there are reasons that each of these definitions are interesting as we visit the discussion of digital twins and human digital twins.

In this document, we will consider a Digital Twin System as including both a real-world entity, i.e., the real-world twin, and a digital representation of the physical or behavioral attributes of the real-world twin. The digital representation we will refer to as the digital twin. These twins are linked together through an interchange component such that changes in one twin can produce changes in the other. As shown in the Block Definition Diagram of Figure 1, Digital Twin Systems typically include a real-world entity, i.e., the real-world twin, and a digital twin where the digital twin is a representation of one or more attributes of the real-world twin. The real-world and digital twins are linked through an interchange component such that changes in one twin can produce changes in the other (Barricelli et al., 2020; Grieves, 2014; Latif & Shao, 2020; Mendi et al., 2021; Sharotry et al., 2020; van der Valk et al., 2020).

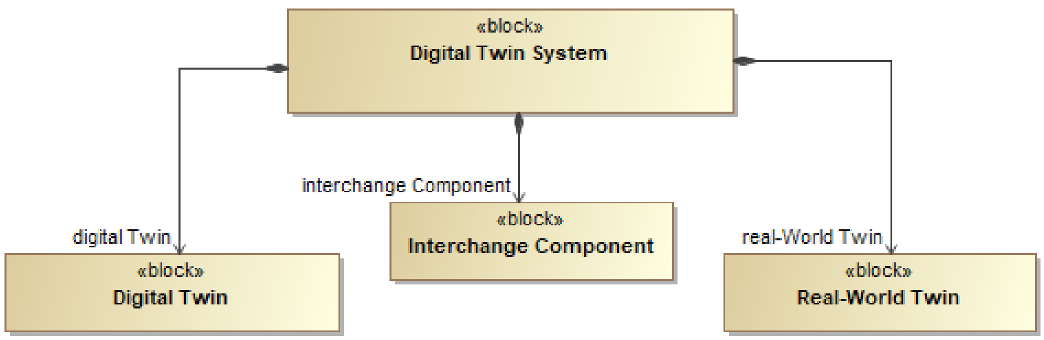

Figure 1. Block definition diagram showing primary components of a digital twin system from literature review.

This interchange component permits the digital twin to be updated as the real-world entity acts within its environment. The digital twin then executes embedded models which are informed by the data it receives from the real-world twin to simulate one or more aspects (e.g., structure or behavior) of the real-world twin with the goal of determining changes in the real-world twin which might produce an improvement in the real-world twin.

To illustrate these components, it is useful to review examples. In the medical field, Chakshu and colleagues envision a human digital twin system in which the real-world human twin is outfit with portable sensors to characterize hemodynamic pressure as a function of time in the limbs of a patient (Chakshu et al., 2021). As this data is collected, it is passed to a model which uses these values together with other characteristics of the patient to estimate the pressure at other points within the circulatory system. These estimates are used to detect the presence or changes in an abdominal aortic aneurism. This system includes predominantly the human with sensors, a data processing system which collects the data and updates the model, and the model and prediction systems which compose the digital twin. However, the authors constrain the environment of use to clinical settings in which the patient is at rest.

Sharotry and colleagues discuss a digital twin system in a manufacturing environment which consists of a human conducting material handling tasks (Sharotry et al., 2020). The system includes a data collection module which includes motion capture, biometric suites among other sensors, a data analysis and forecasting model, and a database which contains the data which is collected for analysis. In this system, performance and operator fatigue metrics are provided to the individuals in the environment to support improved manufacturing performance and to help reduce human injury. Further, this model can be used to identify material handling steps that induce substantial fatigue, permitting these steps to be evaluated and redesigned. Within this example, the real-world twin includes the manufacturing environment, the human, and the data collection subsystems. The database provides the interchange component, and the data analysis and forecasting model provides the digital representation or the digital twin.

As illustrated by these examples, human analysts apply the digital twin to conduct analysis, develop courses of action, and then apply the courses of action in the real world. The courses of action identify potentially useful changes in the structure or behavior of the real-world twin. In these systems, the analyst or the interchange component then causes changes in the real-world twin, which ideally improves the performance of this entity. Importantly, the two-way exchange between the digital and real-world twins provide the digital twin the ability to sense the real world, create an understanding of the world and act upon it, completing a process analogous to the perceptual loop (Neisser, 2014). However, in a digital twin system, this sequence includes a repetitive sequence with the following stages:

1) Sensors on the real-world twin sense the actions and performance of the real-world twin within its real-world environment, as well as relevant state information about the real world.
2) The interchange component conveys the sensed data to the digital twin.
3) An analysis is performed to determine whether the data is consistent with the digital twin's current model projections and adjusts or builds a model to explain any differences.
4) The model is applied to create projections of future behavior within a virtual environment.
5) The projection of future behavior is compared to a goal state.
6) Based on this analysis, the system determines if a modification to the structure or behavior of the system is likely to move the system towards a goal state, and if so, selects a modification to the physical element or its behavior which moves the real-world twin towards the goal state.
7) The modification is conveyed and applied to the real-world twin.

This series of steps is repeated, adjusting the digital models in the digital twin and the real-world twin to move the system towards its goal state. Ideally, the coupling of the digital and real-world twins by the interchange component provides the ability to rapidly create robust models of real-world performance, permit these models to be applied to project future real-world performance, and to improve the performance of the real-world system.

To create accurate predictions, the models not only represent the real-world entity but the environment in which the real-world twin is acting. This fact is not evident in much of the literature as the digital twin concept is applied within controlled environments. Thus, these systems were assumed to be closed; that is, they do not interact significantly with their environment. However, in the applications we wish to consider, the systems are often open, readily exchanging information, energy, or matter with their environment (Blanchard & Fabrycky, 2006). Thus, it becomes important to model the environment to understand the entity's interface with the environment. Specifically, the interface between these components require understanding the spatial configuration, energy, information and material transfer between the environment and the system (Jain et al., 2010). However, from an architectural standpoint, the environmental model does not necessarily need to be part of the digital twin.

Instead, the environmental model may be separate from the digital twin system and simply be associated with this system. This is a significant architectural decision as the human digital twin system will not necessarily require a broad model of the environment but only requires models which reflect the information, energy, and matter that the system exchanges with the environment. Therefore, the complexity of the environmental model may be constrained if it is constructed to capture the necessary elements as opposed to the creation of a more generic and encompassing model of the environment. The real-world twin must also determine the state of the environment and communicate this state to the digital twin.

Reviewing the literature, different components of the digital twin system are illustrated by different authors. Therefore, it is possible to integrate the concepts across these papers to provide an architectural view of a generic digital twin. Figure 2 shows a more detailed block definition diagram based upon an analysis of the digital twin systems in the literature. As shown earlier, this system is comprised of a real-world twin, a digital twin, and an interchange component. However, alluded to before, the real world and a representation referred to as the virtual world are each associated with this system, where these two entities are linked by their state information.

Within the literature, the real-world twin includes a human within the environment. Sensors are used to provide real-time or near real-time information about the human and the environment (Corral-Acero et al., 2020; Sharotry et al., 2020) and this real-time feedback may be augmented with non-real time feedback, such as medical diagnoses, professional electro-cardiograms or information from imaging devices (Corral-Acero et al., 2020). Additionally, the human can be queried to input subjective information (e.g., mood) or information which is difficult to track (e.g., nutrition information) into tracking applications (Barricelli et al., 2020). In manufacturing and product design scenarios, the human also interacts with physical devices (i.e., the system), such as manufacturing equipment, material to be handled, or products which can be instrumented (Barricelli et al., 2020). Additionally, the real-world twin typically includes a process or procedure (Latif & Shao, 2020). Although the process is not a physical item, it is important in understanding the behavior of the human. Finally, while not discussed explicitly in the literature, it may also be important for some mechanism to be present to modify the physical environment. The processes may be changed but to change the physical environment, it is necessary to include physical mechanisms, shown as actuators in Figure 2. As shown, near the head of the arrows associated with these entities, the human digital twin systems, by definition, include a human, one or more sensors, and at least 1 process. The machine and actuators are optional components as they do not exist in all systems, including the sports systems.

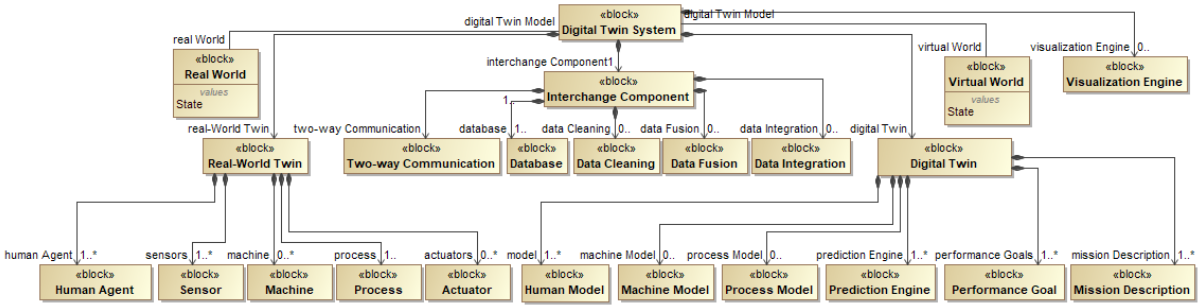

Figure 2. Block diagram showing an exploded view of a generic digital twin system.

Of the three components, the interchange component receives the least attention within most of the published literature. Although the literature is clear that this interchange component permits two-way communication between the real-world entity and the digital entity, its components are not clearly discussed. However, beyond communications, this component can be envisioned as the warehouse for data or the database, although the database is sometimes viewed as part of the digital twin (Latif & Shao, 2020). Further, this component can be responsible for analysis to clean the data, fusing information from the various sensors associated with the real-world twin and integrating new data with the existing data (Tao, Sui, et al., 2019).

Finally, we can review the components of the digital twin within the digital twin system. The digital twin certainly contains a model or representation of the human. This model can include mechanistic models, that model well understood physical, chemical, biological, and physiological processes, as well as, statistical models that rely upon the data collected from the real-world twin (Corral-Acero et al., 2020). It can optionally contain additional models of the machine or the process to be performed (Latif & Shao, 2020; Tao, Sui, et al., 2019). Also necessary is a prediction engine that generates perturbations to the virtual world, human, machine, or process to understand how changes in these elements affect the performance of the human or the system (Tao, Sui, et al., 2019). To assess the outcomes, a functional goal is also required such that the results produced by the prediction engine can be assessed. A mission description is also likely necessary to inform the process model of potential process steps.

Although not shown in Figure 2, it is also common for a process manager to interact with the digital twin to determine if any of the modifications evaluated by the prediction engine should be applied to the real-world twin. While these modifications may be communicated through the interchange component to the real-world twin, physical changes to the real-world twin may require human intervention.

It is worth noting that during design the real-world twin may be under development and therefore the real-world twin or even a prototype of the real-world twin may not exist to participate in the digital twin system. Under these circumstances, and perhaps others, it can become useful to include the visualization engine, as shown in Figure 2 (Havard et al., 2019; Ma et al., 2019; Wang et al., 2021). This visualization engine can provide a virtual or augmented reality rendition of the digital twin in the virtual or real worlds which a designer or potential user can interact with to improve insights and understanding until the real-world twin is available.

1.2 Literature Related to Human Digital Twins

Although significant work has been performed on digital twin systems across a range of industries, it is more difficult to find literature that directly discusses digital twin technology applied to improving or understanding human attributes. An initial review of this literature shows that these systems can be focused either directly on the human or upon processes in which humans participate. The systems focused on the human are often focused on improving the physical performance, health, cognitive, or emotional performance of the human (Barricelli et al., 2020; Chakshu et al., 2019). While systems focused on processes in which humans participate are generally focused on the design of systems involving humans but have significant components dedicated to capturing attributes of the human (Caputo et al., 2019; Sharotry et al., 2020). This later class of systems are consistent with the use of general digital twin systems in the literature and do not focus on models of the human.

The distinction between human digital twins as stand-alone models of the human and digital twins being components within a larger framework is an important distinction. Fundamentally, if one could construct standalone models of the human which were general enough, these models could be embedded into system models or human digital twin systems to assess a variety of systems. This requires a change in our vision of a human digital twin system as shown earlier. Perhaps a broader conceptual framework would include a framework as shown in Figure 3.

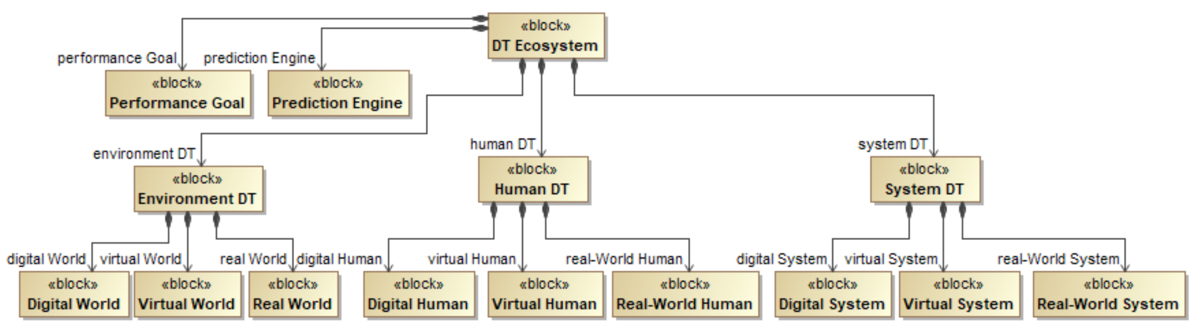

Figure 3. Block diagram of digital twin infrastructure, illustrating independent human digital twin.

As shown in Figure 3, we can define a digital twin ecosystem, that includes digital twin systems of environments, humans, and machines or tools. As shown, each of these digital twins include a digital, a virtual, and a real-world component. The digital component represents mathematical models and the ability to use these models to project future events. The virtual component represents the ability to render representations of the entity as a virtual entity. The real-world component represents the physical embodiment of the system. Ideally within this framework, components could be mixed and matched, perhaps somewhat analogously to live, virtual, and constructed entities that are applied in training simulation. This ability would permit a human to interact with a virtual system within a virtual environment, to place a virtual human in a virtual system during early system evaluation and assessment, for a multitude of other reasons, including training. In this representation, the human digital twin would include models that support both the digital and virtual humans.

1.3 A Proposed Definition of Human Digital Twins

Based upon the prior discussion, we can attempt to define a human digital twin and a human digital twin system. We need to consider several aspects to define the human digital twin. It is clear based upon the literature that a Human Digital Twin Systems (HDTS) should include a digital representation of a real-world human. This real-world human may be an individual, whom we wish to characterize and model or a human class, where this human class represents a group of humans with common traits, characteristics, behavior, etc. The Human Digital Twin (HDT) is then the digital representation of the real-world human or real-world twin. The HDT may exist purely as a mathematical representation of the individual or class of individuals. Alternately, the HDT may exist as a virtual entity that can be rendered within a virtual or real-world system.

The digital representation can include both first principles models based on fundamental understanding and statistical models. Various attributes of one or more humans can be modelled (Alexander et al., 2020). These include attributes in at least one of the following categories:

a. Physical: including anthropometric attributes, biomechanics attributes, times required for task completion, eye movements, and injuries
b. Physiological: These attributes include low level measures such as heart rate, heart rate variability, galvanic skin response, muscle tension, blood oxygen level, brain electrophysiologic signals, pupillometry, blink rates and timing, peripheral blood flow, gastronomical activity. However, these are intended to correlate to higher level physiological measures such as fatigue, circadian cycle, alertness level, activation or engagement level, among others.
c. Perceptual performance: auditory sensitivity, ability to decipher speech in different languages, visual sensitivity, color sensitivity, contrast sensitivity, pressure sensitivity, pain thresholds, temperature sensitivity, etc.
d. Cognitive performance: knowledge, skills, abilities or aptitudes, workload level, situation awareness, decision making abilities, intuitive/analytic bias, etc.
e. Personality characteristics: These attributes include personality type, propensity to trust, propensity towards suspicion, etc.
f. Emotional state: feelings experienced by the individual within their current circumstance, including levels of depression, anxiety.
g. Ethical stance: representation of the individual's belief system, including values, beliefs, and mores.
h. Behavior: actions taken by the individual to interact with the system. These actions may be influenced by any of the earlier attributes.

As such, we can define a human digital twin as an integrated model that facilitates the description, prediction, or visualization of one or more characteristics of a human or class of humans as they perform within a real-world environment. A human digital twin system is a pairing of a real-world human twin and a human digital twin that includes a model of physical, physiological, personality, perception, cognitive performance, emotion, or ethics of a human; where the real-world human and human digital twin are integrated such that a change in the real-world human or its digital representation produces change(s) in the other. This human digital representation likely includes both mechanistic and statistical models of one or more attributes related to one or more of the human defined properties.

1.4 Use Cases of a Human Digital Twin

Besides defining HDTSs and investigating their structure, it is also useful to understand how they might be applied. Within the literature, use cases are discussed or the health industry where HDTSs support well-being, health care, and development of medical devices (Laamarti et al., 2020). Additionally, use cases are discussed for the design and manufacturing of products, including design of human-machine interaction, as well as the development of product service and use (Ma et al., 2019).

For product development and application, use cases may be considered for different product lifecycle phases, that is, they may be useful during product design, verification and validation, manufacturing, and use. Although HDTSs might be useful during any phase of the lifecycle, Figure 4 and Figure 5 depict the use cases that apply during product development or acquisition, and operations and sustainment, respectively.

As Figure 4 shows, during the product development and acquisition life cycle phase, HDTSs can be used to aid the design of various portions of the system to be acquired. This might start with simulation of the human operating the product within the System of Systems (SoS) to understand operational needs and the benefits of enhancements. As these needs are defined, modifications or new product concepts may be developed and evaluated (Laamarti, 2019). In this use case, models that exist within the human digital twin can be applied early in system development to evaluate the utility of various designs and to analyze the impact of these differences through trade space analysis (Tao, Zhang, et al., 2019). This might include evaluation and understanding of various manpower, personnel, and training options, as well as options regarding the performance or other attributes of the system which impact important emergent behaviors, i.e., "ilities" of the system. Further, these models might consider modifications to the user interface, items that enhance human physical or cognitive performance, as well as personal protective equipment (PPE) to prevent performance degradation. Perhaps some models might be applied to understand the tradeoffs in operator or maintenance procedures to aid mission design or to optimize the performance of operators or maintainers within the system. As further indicated in this diagram, these models and HDTSs will likely require sharing and collaboration among different communities that interact during product design and acquisition.

It should be noted, that early in a development cycle of a novel product, the real-world portion of the HDTS will undergo design and therefore, the real-world system or representative, trained operators may not exist. Thus, a representative real-world system will not be available. During these portions of the lifecycle, the digital portion of the HDTS will be required to operate in an open loop fashion. However, as prototypes of portions of the system are developed and early proxies for system operators and maintainers are used to participate in demonstrations, simulations, or evaluations, data from these events can be used to begin to close the loop from the real-world to the digital models for the system and the humans. As this data is included, the level of model fidelity and user confidence in these models should improve. Besides changes in model fidelity, the level of detail represented by the models is likely to change as one progresses through the system development and acquisition process from early needs development through acquisition. Similar models can also be applied during development of the manufacturing and logistics processes to affect human interaction as development of the real-world twin.

As the system enters operations and sustainment the use cases depicted in Figure 5 become relevant. In this phase, the focus of HDTSs shift from focusing on changes to the material components of the system to focusing on changes in the Tactics, Techniques, and Procedures (TTPs) that are employed when applying the system. Similarly, these models may be used to evaluate and improve training or personnel selection methods (Ma et al., 2019). Additionally, the Human Digital Twin may be used to understand readiness of personnel who interact with the systems or understand the errors or circumstances in which errors are made (Tao, Zhang, et al., 2019). Finally, the HDTSs may be applied in real time to determine and allocate taskwork among team members (Ma et al., 2019). The corresponding use cases are shown in Figure 5.

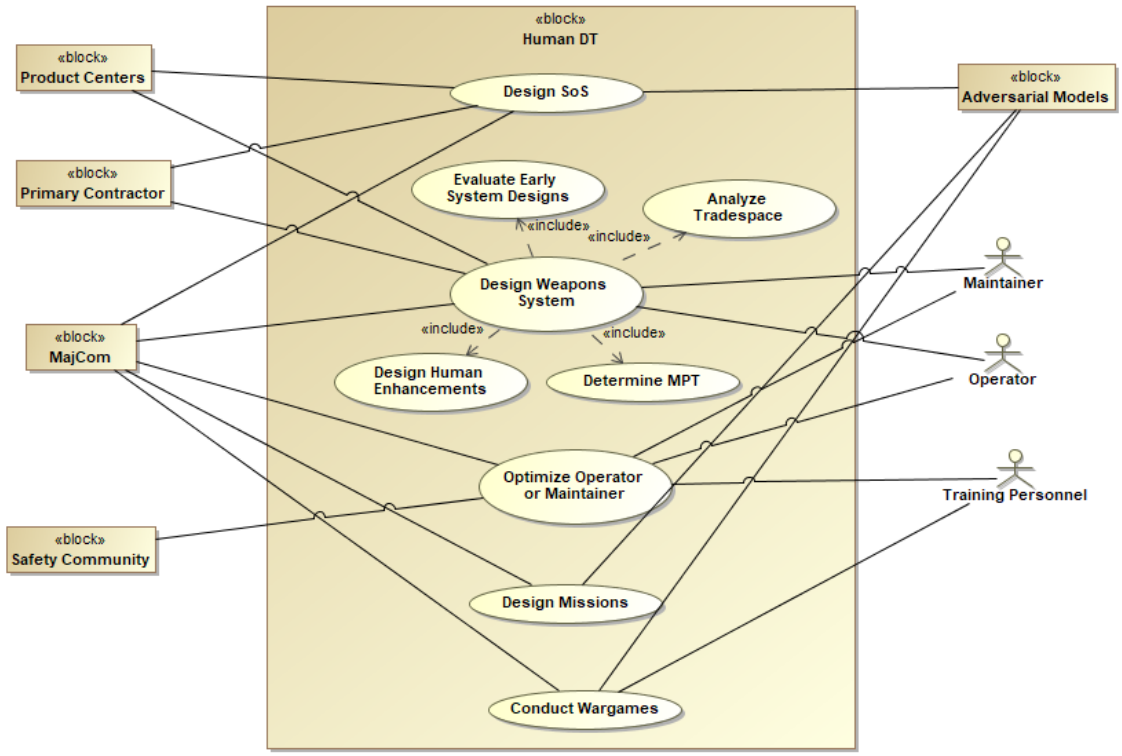

Figure 4. Acquisition based Use Cases developed from brainstorming and literature.

As shown in Figure 5, as the HDTS is deployed with the system to the field, we expect that the operators will develop and employ new or revised TTPs that increase the utility and performance of the product (Cox & Szajnfarber, 2017). The resulting innovations help to redefine taskwork and improve training. Further, the models themselves may be used to explore changes to taskwork beyond those captured from observing user behavior, as observed in the manufacturing-oriented literature. Additionally, the HDTSs may be employed to analyze and understand human errors, that result in either near misses or mishaps to suggest changes in TTPs, training, or taskwork to improve safety. Further, utilization of personal protective equipment, as well as environmental exposure to information, energy, or matter (e.g., radiation or known carcinogens) may be monitored to support occupational health interventions. Further, the HDT may be capable of understanding attributes of the humans which enhance performance, aiding refinement of personnel selection.

Although TTPs, training, and personnel selection may all improve system performance, perhaps the greatest opportunity is understanding human readiness. However, this use case likely diverges significantly from the human digital twins that would be useful during system development. In fact, this use case likely relies upon significant interaction with the management and medical personnel who are not as likely to interact with the other use cases illustrated in Figure 5. Although not apparent from our earlier discussion, the HDTs applied in medical and sports performance focus on understanding performance of systems which are internal to the human while HDTs applied in product design or manufacturing tend to focus on human behavior and the interaction of the human with systems and the environment. As such, there is a basis for arguing that the HDTs used for understanding readiness may be unique from the HDTs used for practically all other use cases shown in Figure 4 and Figure 5. Nevertheless, each of these HDTs rely on input from the same real-world humans and the HDT models within these two areas certainly interact. Therefore, a HDT developed to support readiness and HDTs developed for other use cases will likely require some level of integration. Thus, there will be a need to integrate models of the human which are intended to understand health or health related human performance with models of the human which are intended to understand their performance when interacting with systems within an environment.

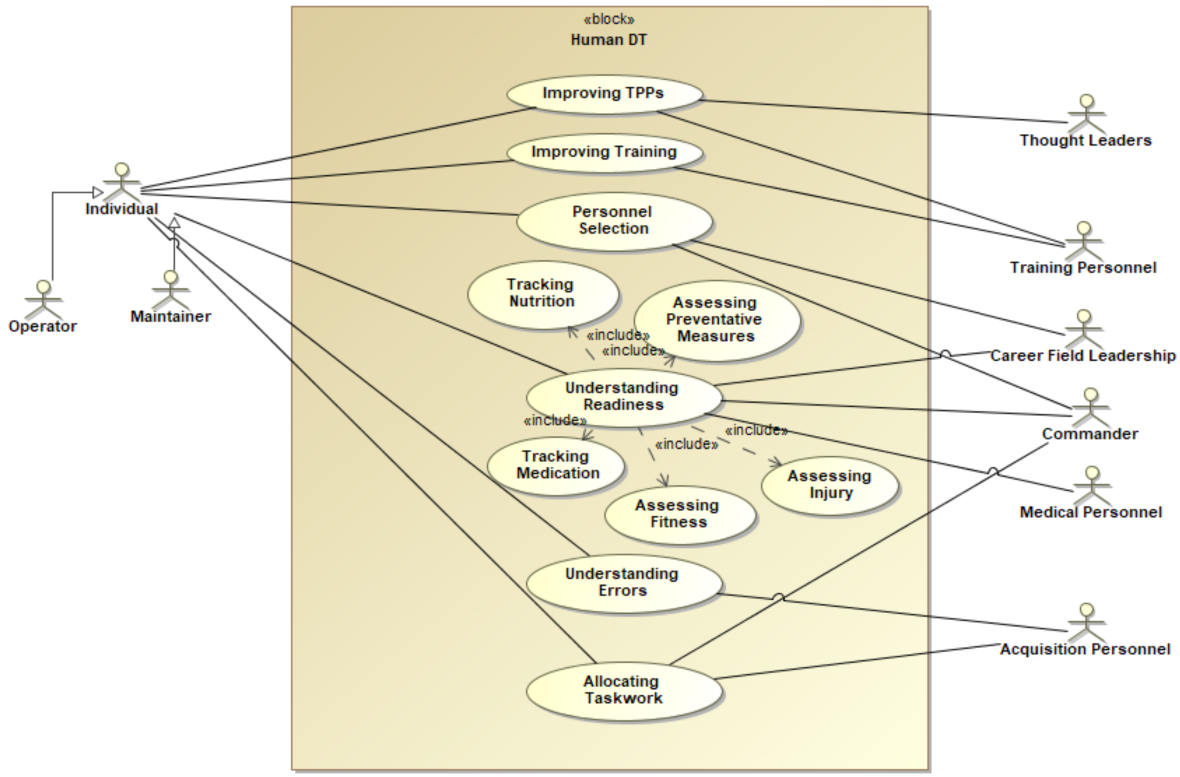

Figure 5. Operations and Sustainment use cases imagined based upon literature.

2 Systems Views and Viewpoints of Human Digital Models

The development of HDTSs as described earlier requires the development of multiple components, including models or representations of the human, sensors to understand attributes of the real-world human, their interaction with systems and the real-world and mechanisms for implementing changes to the real-world human or system as improvements are determined from the model. Additionally, technology components are required on the digital side of the HDT, including secure warehousing of human data to support the HDT. Despite the large range of needs, here we focus specifically on the models within the HDT or Human Digital Models.

2.1 Model Context

To begin to develop a model to support development of a human digital twin that targets the acquisition process, it is useful to define a model framework that can be integrated with design languages such as the Systems Modeling Language (SysML) (Delligatti, 2013; Friedenthal et al., 2014). However, this modeling language was designed to describe systems and does not necessarily provide robust frameworks for modeling the human or the interaction between the human and the system. Thus, extensions to this language have been discussed (Miller et al., 2020; Orellana & Madni, 2017; Rountree & Thomas, 2021). Further, it is important to establish a context for these language extensions.

One context for the integration of human model artifacts into the SysML framework was proposed by Orellana and Madni (Orellana & Madni, 2014). An extension of this framework is proposed as illustrated in Figure 6. Figure 6 shows the real-world components in gray and the modeling components in tan. Important to modeling the performance of the system is modeling the performance of system artifacts (e.g., hardware, software, etc.) as well as the human agents who interact with the system. Under some circumstances, it may be important to understand that these human agents work within an organization. Both the system and the human agents may interact with the environment as well as other systems that comprise a system of systems.

Moving to the modeling artifacts, the system model is constructed to conform to SysML. The model describes the system architecture, which may comply to an architectural framework, such as DoDAF or some other architectural description. The system model may be viewed through several viewpoints which support system analysis during the system design process.

From the human point of view, one or more human models may be integrated with the system model to provide viewpoints and additional system analysis. As SysML does not provide an adequate description of the human, it will be necessary to extend SysML through methods such as a human profile. Such a profile or related tool extends SysML to include the language constructs necessary to support the development of the human model. In developing the human profile, it is useful to develop a metamodel that describes the interaction of modeling components within the human profile and a human ontology, that describes the modeling components within the metamodel and the human profile. The development of this ontology and metamodel is important as they serve the basis for representing the human within the model which then provides a framework to support development of the human model.

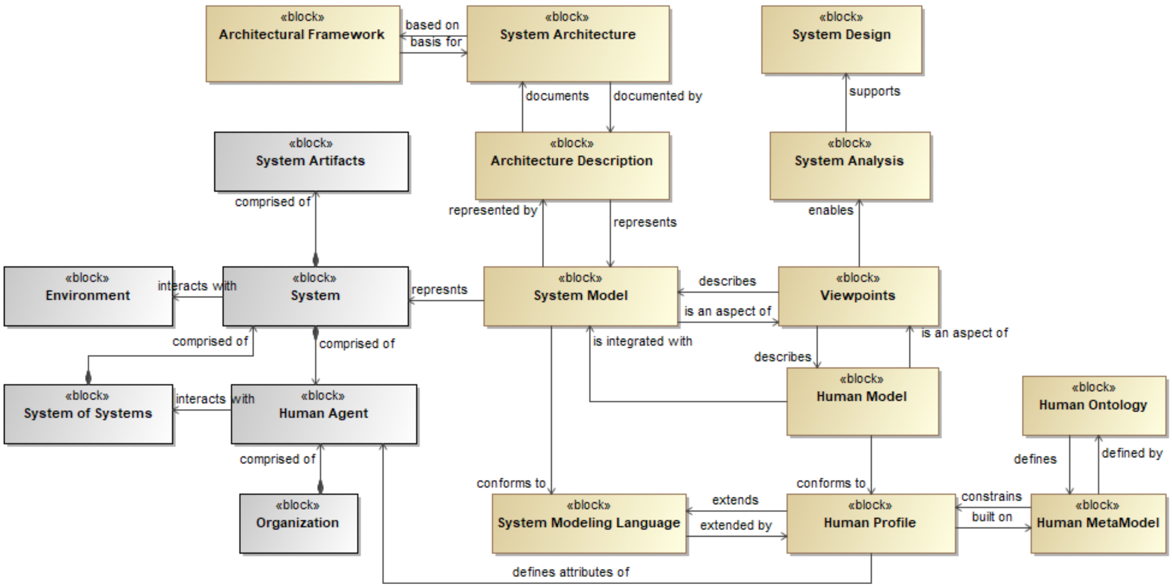

Figure 6. Modeling context diagram illustrating the real-world entities (shown in gray) and modeling artifacts (shown in tan).

2.2 Human Model Ontologies

Reviewing the literature, human ontologies have been previously proposed for use in system models. For example, Orellana and Madni propose an ontology where the human agent is modeled as having roles and skills (Orellana & Madni, 2017). Their behavior is modeled through functions, state machines, and operations that permit parametric analysis resulting in task analysis, workload analysis, and cognitive analysis. Orellana and Madni also show mechanisms such as human system verification, limitations, and human system integration procedures. This same ontology is echoed by Rountree and Thomas (Rountree & Thomas, 2021). In a separate paper, Orellana and Madni propose a human-system integration profile (Orellana & Madni, 2017). In this profile, the authors define a Human-Agent stereotype based upon physical characteristics of the human, Human Tasks with associated performance measures, and Human Functions, which are activities composed of an array of human tasks. The stereotype also includes several operations, including visual, motor, auditory, speech, and cognitive. Although each of these models have some interesting characteristics, neither is illustrated to demonstrate a robust human model. In fact, the ontologies of both, often include both human and system elements (e.g., human interface elements). They each suggest that there is a need for metrics of human performance, an understanding of the mechanisms to associate human capabilities and limitations to support human system verification and integration, and the need to understand how human roles and skills couple with interface elements to result in human behavior.

A metamodel for modeling human behavior and cognitive activity has also been proposed (Miller et al., 2020). In this model, it is recognized that humans interact as teams with systems and artificial agents to achieve goals. As they seek to fulfill their goals, they fulfill assigned roles as team members to achieve their goals. These roles make the individuals responsible for activities during which they employ specific capabilities which are derived from training and procedures. These responsibilities are fulfilled by performing activities within specified scenarios, where these scenarios include activities situated within an environment. This model does not explicitly capture performance, but it recognizes that humans often exhibit goal-seeking behavior and, although they can rely on procedures to provide repeatability, they can also rely on training to craft alternative procedures to achieve their goals. These models do not capture the fact that humans often modify their behavior based upon perceived constraints within their environment. This is a significant limitation as constraints on time, physical resources, and information often require the operator to devise new procedures to increase their ability to achieve these goals.

In these models it is useful to investigate the metrics which may be useful when modeling the human as part of the system. It is important to focus on performance measures and other metrics that can be used to judge overall system performance. Additionally, it will be useful to characterize human state information where these states influence the performance of the human in these systems. Finally, we need an array of data structures and modeling patterns that facilitate calculation of system performance.

2.3 Human-Relevant Metrics

To understand what we wish to model, it is useful to consider the measures or metrics that can be used to understand both the performance of the system and the "goodness" of the interface between the human and the system. In this section, we derive and discuss an ontology for human-relevant metrics. An overview of the ontology is provided in Figure 7.

2.3.1 System Performance Metrics

Overall system performance is often characterized in terms of Effectiveness (i.e., the likelihood of successful mission completion) and the Efficiency (i.e., the physical resources such as manpower, number of systems, energy, time, monetary expenses necessary to complete the mission) of the system. Hitchens argues that while these metrics are useful when examining a system operating in an environment from an external view, these metrics can be misleading when examining a subsystem within a larger system (Hitchins, 1992). Instead, Hitchins argues that one should focus on the contributions of the system to the overall organization (i.e., system of systems) goals, understanding the capacity of the system to support the goals of the enterprise or the System of Systems and the costs the system imposes on the larger organization.

In traditional human factors, human task times are often used as a measure of efficiency and human error rate is often used as a measure of effectiveness. However, depending upon the system configuration and bottlenecks within the system, these metrics may or may not affect the overall efficiency or effectiveness of the system in which the human is embedded. Thus, a broader viewpoint will often be necessary to understand the effects of human performance on system performance.

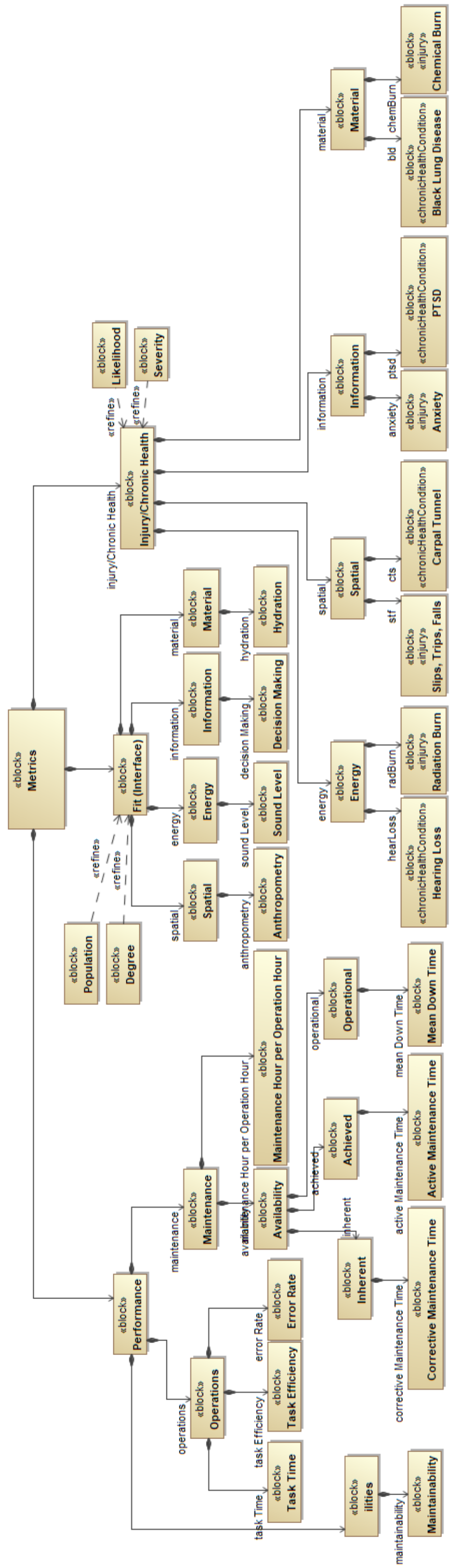

Figure 7. Proposed taxonomy of human-related metrics.

Often human performance is modeled using a series of tasks that the human executes in concert with activities and actions performed by the system. This is consistent with several modeling approaches, including simple activity modeling embedded in SysML tools. It is also prominent in various human modeling techniques, including the Improved Performance Research Integration Tool (IMPRINT) that supports the discrete event simulation of tasks with variable performance times for either the human or the system. Each human in IMPRINT has associated workload, task timing, fatigue, physical or cognitive limitations, among other attributes. This goal and task-centered modeling approach has been applied to understand human interaction with systems as well as the time required for an operator within a defined system to perform a series of tasks (Colombi, J.M.; Miller, M.E.; Schneider, M.; McGrogan, J; Long, D.S.; Plaga, 2011; Rusnock & Geiger, 2016; M. Watson et al., 2017; M. E. Watson et al., 2017). IMPRINT additionally provides a crude mechanism for modeling goals with different priorities, where each goal is decomposed into a series of tasks with each task having associated time and workload requirements. Theoretically, these goals could each be achieved by one of multiple potential sequences of tasks and these sequences of tasks could be selected based upon known constraints, such as workload or time constraints (Geddes, 1989). However, the task sequences are hard coded into the model and thus these models do not exhibit adaptive behavior beyond that which might be envisioned by the modeler. Further, construction of these task sequences requires time. Thus, the standard approach is to model only the sequence of tasks prescribed within standard checklists.

Cognitive models that attempt to provide more flexibility in operation have also been proposed, such as the Adaptive Control of Thought-Rational (ACT-R) model (Anderson et al., 2004). However, these models have been applied predominantly to model relatively simple laboratory tasks and will likely need significant modification to use in existing system models. However, the real time data collection provided by digital twins might aid the further development of this type of model.

Each of the metrics discussed earlier are often difficult to assess when performing capabilities-based assessments where the capabilities of any system can potentially impact several missions, in which the operator may situationally prioritize different goals at different times and the importance of each of these missions may not be understood. We can evaluate the net contribution, effectiveness, or efficiency of a system within any mission context but as these may vary across mission contexts, an overall metric is perhaps difficult to obtain.

While these metrics apply to the operator's performance as a component of overall system performance, other metrics may apply to other human roles. In maintenance, the overarching metric of interesting is system availability; which is often described using one of three metrics; including inherent availability (A_i), achieved availability (A_a) and Operational Availability (A_o) (Blanchard & Fabrycky, 2006). Each of these three metrics apply a ratio of up time to the sum of the up time and a metric of maintenance time. These metrics are described as follows. The first of these is A_i, which is defined as:

$$A_i = \frac{MTBF}{MTBF + \bar{M}_{ct}}$$

Where MTBF is the mean time between failures and $\bar{M}_{ct}$ is the mean corrective maintenance time. Note that this metric does not include preventative maintenance but assumes that the system is operational and available anytime that it has not encountered a failure. A more encompassing metric, A_a additionally includes preventative maintenance activities.

$$A_a = \frac{MTBM}{MTBM + \bar{M}}$$

where MTBM is the mean time between maintenance and $\bar{M}$ is the mean active maintenance time, where this mean is calculated across both preventative and corrective maintenance actions. Operational availability further considers the fact that maintenance is often delayed by the lack of resources, including parts or supplies which occur due to logistics delays and the lack of assigned maintainers that occurs due to administrative delays, which can occur for multiple reasons, including lacking adequate numbers of trained maintainers to complete all maintenance tasks. This value is computed as shown below.

$$A_o = \frac{MTBM}{MTBM + MDT}$$

where MDT is the mean down time which includes not only the active maintenance time but the logistics and administrative delay times which occur during system operation. Each of these metrics are often listed as a key performance parameter of a system and the time spent in maintenance is important to each of these metrics. However, these metrics only inform the operation of the overall system but do not provide insight into the true cost of maintenance as these times can often be reduced through increasing the size of teams of maintainers. Another system wide metric which provides insight into the true cost of maintenance is the ratio of the number of maintenance hours per hour of system operation. Thus, the time spent by individuals performing maintenance informs each of these metrics. Times can again be estimated based upon task-based approaches, as discussed earlier. Design activities which focus on elimination of tasks, such as changing tools during maintenance has been shown to significantly impact maintenance time (K. K. Liu et al., 2010). These metrics of course speak only to the time spent to perform the work without considering quality and thus other metrics, such as errors per maintenance hour might provide insight in the quality of the work.

In most systems, human performance is predominantly within the Human Factors Engineering domain of Human Systems Integration. However, overall system performance can be impacted by changing the number of individuals interacting with the system, which falls in the HSI domain of Manpower, or the development and skill level of these individuals, which falls into the HSI domains of Personnel and Training.

2.3.2 Environmental Interactions and the "ilities"

Returning to the taxonomy of measures and further examining the performance branch, the taxonomy includes one additional category of metrics, referred to as "ilities". Like the performance measures, the "ilities" are not understood from the attributes of the system directly. Instead, the "ilities", like the other metrics are emergent properties of the system. They appear as properties of the system which can only be observed by coupling the components of the system together and permitting them to interact, not only with each other but the environment in which the system is situated. The "ilities" represent attributes of the system which have value to the stakeholders and generally permit one to represent performance of the system across a wide range of contexts. As McManus and colleagues discuss, system success depends upon the user's needs, the context of use of the system, and the form of the system. Further, McManus and colleagues discuss the fact that it is the dynamics among these factors which "determine the perceived success of the system" and the "ilities" provide a means of expressing the performance of the system in response to the user's needs and the context of use of the system (McManus et al., 2007).

To illustrate this concept, we can consider maintainability. Blanchard and Fabrycky define Maintainability as "the ability of a product to be maintained". These authors discuss the fact that various figures of merit can be used to quantify maintainability, including the probability an item will be restored to a specified condition in a given period of time, the probability that maintenance will not be required more than a given number of times in a given period, or the probability that the maintenance cost will not exceed a specified cost (Blanchard & Fabrycky, 2006). While the metric of Mean Down Time is most related to the higher-order "ility" of Availability, the fact that these different figures of merit exist are important. In fact, the differentiation between the duration and frequency of maintenance expresses the fact that maintainability can be influenced at different temporal stages in a process. That is, we can gain increased maintainability by requiring less frequent maintenance through measures, such as increasing system reliability, or by streamlining the maintenance process to decrease the required maintenance time.

Temporal dependence is one of the consistent attributes of "ilities" as is the environmental influence. Within maintainability, we might consider two separate inputs to discussing and quantifying "ilities", including the time sequence during which activities related to the "ility" occurs and the environmental context (McManus et al., 2007). For maintainability, the time sequence may begin with the steady state use of the system, include identifying the need for either preventative or corrective maintenance, presenting the aircraft to the appropriate facility for maintenance, diagnosing the steps necessary for maintenance, obtaining supplies to perform the maintenance, conducting the maintenance, and then returning the aircraft to operational status at the point of use.

Besides the temporal dependence of the "ilities", the environmental context influences each of the 'ilities" (McManus et al., 2007). Thus, a description of the environment will be required to understand each of the "ilities". This environmental context for maintainability or availability will typically include both the frequency of use of the system, which will influence the time between corrective maintenance actions, and context of use of the system. For example, the environmental context for military system the types and frequency of missions which may result in various degrees of damage from adversarial forces. The latter item then aids the understanding the types of maintenance activities that will be required. To improve maintainability and availability, it will be desirable to perform frequent maintenance activities quickly while perhaps permitting infrequent maintenance activities to require longer periods of time.

Estimation of these desirable emergent system properties or "ilities" are important when performing trade-off analyses (Parnell et al., 2021). These tradeoff analyses have been addressed in the literature by multiple authors (Colombi et al., 2014; Ross, 2006). The process models proposed by Colombi and Ross with their colleagues were originally developed to facilitate trade space analyses for spacecraft. However, they can be applied equally well to human-centered "ilities", such as maintainability. An adaptive version of the process for performing these trade off analyses as proposed by Colombi and colleagues is shown in Figure 8.

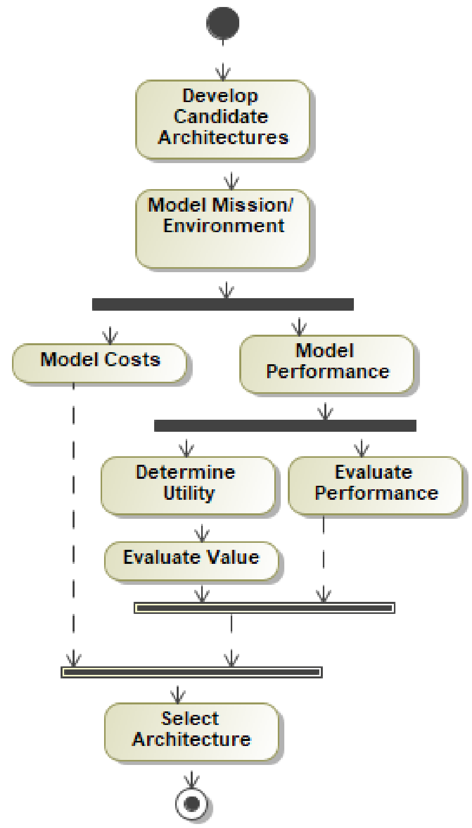

Figure 8. A process model for performing tradeoff analysis, adapted from a method discussed by Colombi and colleagues (Colombi et al., 2014).

As shown, the first step in this process includes developing candidate architectures. In a maintenance example, this step might include variations where one aircraft system has a higher reliability than another or it might include systems where all recurring maintenance is performed in a deployed environment, as opposed to systems where some recurring maintenance is performed in a deployed environment, while other activities must be performed in a centralized depot. Initial definition of these architectures is important as the available options define the scope of the models which must be constructed. In this example, the model will need to account for differences in reliability, frequency, and location of maintenance activities. Note that while each of the different architectures are described as being distinctly different, this technique may be more powerful if the items are thought of as differing on a continuum. For example, reliability may vary according to a continuum or the specific types and numbers of maintenance activities which are performed in a depot versus a fielded environment. In yet another architecture, the interfaces to the human operator might be designed to facilitate maintenance with a small number of tools which provide quick access to modular components versus systems which are designed without attention the factors which might lengthen the duration and complexity of maintenance operations. In this case, the model will need to permit one to understand how these changes to the system-maintainer interface affect the overall maintenance time.

The next step is to model the missions and environment for the system. In the example, this model might include estimates of the number of flight hours per period, which permits estimation of the frequency of required maintenance as well as the types of maintenance activities. It might also include an environmental model, which permits understanding of likely damage the system may incur during use.

From this model, a pair of additional models may be created as shown in Figure 8. The first will estimate the cost associated with that system architecture. From a human perspective, these costs will include the number of personnel required to maintain the aircraft as well as logistics personnel required to support these maintenance activities. They may also include the costs to obtain and sustain the maintenance workforce, including costs associated with personnel acquisition, training, and support.

The second model will be a performance-based model. In the example, this model might estimate the time required to perform the maintenance activities, which, when combined with the frequency of the various maintenance activities provided by the mission or environmental model, will permit estimation of metrics associated with maintainability. Note also that these metrics then provide values such as mean down time which informs higher level "ilities" such as availability.

As a result of the performance-based model multiple performance metrics can exist. The system may be evaluated based upon each of these performance metrics. This may be important as a minimum level of performance for one or more of these metrics may be required. Simultaneously, a utility model may be developed which permits one to collapse the multiple performance metrics to a single value metric. This model assesses the utility as a function of each performance metric and permits these functions to be combined into a single, often weighted metric. Each of these metrics may then be plotted as a function of cost to facilitate the tradeoffs between performance and cost of the individual architectures to facilitate the selection of architectures to explore further.

It is also important to understand that many of these metrics interact, increasing the complexity of system evaluation. For example, Figure 9 shows a portion of a causal loop diagram which relates some of the metrics we have just described with other system attributes or "ilities". As shown in this figure and as expressed by the operational availability metric, reliability, supportability, a measure relevant to logistics, and maintainability, all influence availability. Maintainability may also be influenced by the ability to test the system, train individuals, effect specific repairs, and modularity, which reduces maintenance time by permitting faults to be tracked to subsystems rather than components. Modularity can also influence trainability and testability. In an aircraft, increasing modularity unfortunately can negatively affect overall system performance through addition of mass and volume. Therefore, there is a balance between the measures used to improve system performance through increases in availability and measures used to improve modularity, which can significantly improve availability but also decrease system performance.

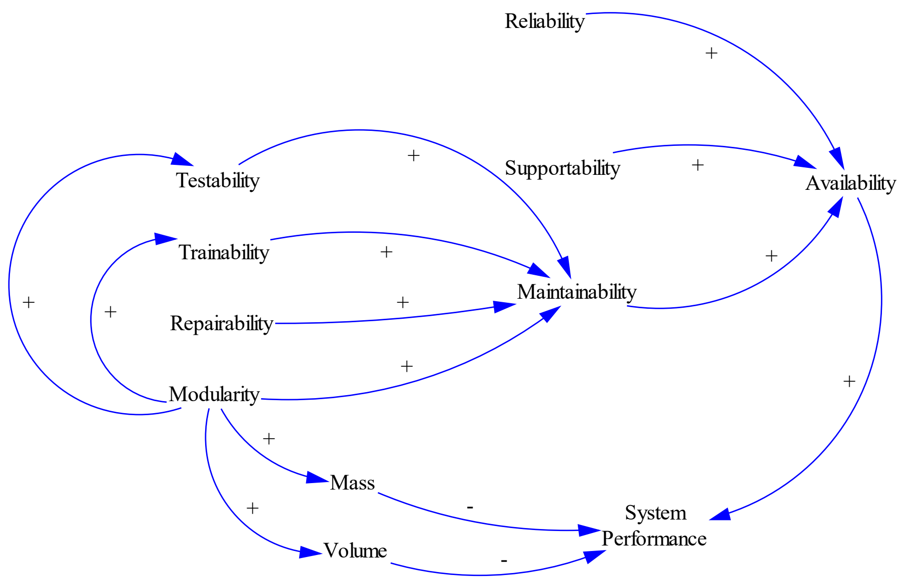

Figure 9. Diagram depicting a portion of the influences and interactions between modularity and availability on system performance as it pertains to maintenance activities.

Often desirable emergent system properties, such as repairability, is influenced by measures of fitness as well as understanding any risks that the system or environment imposes on the human.

2.3.3 Metrics of Fitness

Measures of fitness are an expression of the interface between the human and the system. As Jain discusses, interface requirements can be understood in terms of Spatial, Energy, Information and Material transfer between any two system elements (Jain et al., 2010). Similarly, the fitness of the interface between the system and the human can be quantified in terms of these four general categories. Although material transfer is less common in human-machine interfaces it can occur, for instance, when transferring material to the person for health care or providing oxygen or water, as well as removing urine when operating in high performance aircraft are examples.

When discussing fitness, anthropometric dimensions, which specify one part of the spatial requirements, may come to mind for many individuals. To assess whether a workstation can accommodate a range of individuals, it is modern practice to select representative individuals who lie near the population boundary of individuals as it has been shown that few individuals have dimensions near the mean (Daniels, 1952) and the dimensions are loosely correlated among individuals (White, 1961). For example, when evaluating reach envelopes, individuals might be selected who represent different extremes within a two-dimensional space including arm and torso lengths as the length of each of these body segments can influence reach distance and the two dimensions may not be highly correlated with one another. Models might then be created which represent the upper bodies of individuals at multiple, relative extremes (e.g., to include 95% of the aim population) in this two-dimensional space and these models might be used to determine which objects in the workstation the modeled individuals can reach while seated (Committee, 2004; Jung et al., 2021). Workstations which accommodate the models are then judged to be "fit" for use by the desired user population. This anthropometric fitness is an important attribute of fitness in which the dimensions of a human workstation within a system provides the ability to accommodate the variability in physical dimensions of the human operators. Efforts to accommodate this variability in physical dimensions date back to the 1960s for the design of aircraft cockpits where requirements were placed on the design of aircraft requiring the cockpits to accommodate humans with a broad range of anthropometric dimensions, permitting individuals with a large range of anthropometric dimensions to fit into and thus perform well within the cockpit. Similar fit metrics are relevant to maintenance as it is important for a range of maintainers to fit inside the system to access components or modules which frequently require maintenance.

Moving from physical to energy fitness, we can discuss energy of visual or auditory stimuli as examples. Human visual and auditory systems are capable of sensing certain energy ranges of visual or auditory stimuli under specific conditions. The ability of the system to deliver the appropriate energy to facilitate human performance can serve as another example of fitness. While systems which provide perceptual stimuli are rarely designed to accommodate a given range of people using analogous design principles, controls are often provided to the users to adjust the range of perceptual stimuli these systems produce, permitting the systems to accommodate a range of operators within a range of environmental conditions.

In terms of information, we can consider whether the information transfer between the system and the human is appropriate. For example, we might ask is the correct information available to the user to support appropriate decision making? We might also consider the task load a system imposes on a user in terms of fitness. Expert users may perform well under high task load conditions while novice users may be incapable of responding well to these high task loads. Of course, a portion of this task load occurs as the human must interpret information from the system.

As stated earlier, purposeful material transfer between a system and a human operator is less common. In advanced aircraft, the aircraft provides oxygen and removes carbon dioxide as well as provides mechanisms to provide drinking water and to support the removal of urine. For oxygen we can provide either too little oxygen, leading to hypoxia, or too much oxygen, leading to hypercapnia. Therefore, as is the case for other variables of fit, appropriate design of delivery systems is critical to supporting the user.

It is also important to realize that many dimensions of fitness may depend upon human state information. For example, the cognitive capabilities of a human may be matched to the cognitive load imposed by a system when a person is well rested, providing a good fit to the human operator under this cognitive state. However, this system may not provide a good fit to a person who is experiencing a low level of alertness or arousal or a high level of fatigue.

Fitness and performance are related as performance generally improves as the fit between a specific human and the system improves. We can think of the influence of fit using the causal loop diagram in Figure 10. As shown, fit may be considered in at least two different contexts. One method is to simply define fit based on an individual's ability to use the system to achieve at least some defined level of performance, e.g.., reaching the controls on the workstation without releasing weight from a seat. This context is illustrated through the top loop in Figure 7 whereas fit increases the proportion of the available human population which can achieve this desired performance level increases. For a given population of recruits and required manpower level, this permits manning or the proportion of the billets available within a related career field to increase. This proportion is also increased as we expand the number of potential recruits but decreases as the required manpower increases. Increases in manning leads to improved human performance as the available people can fulfill their training requirements, have proper work-rest schedules, etc. Fitness can alternately be defined to aid the human in obtaining near peak performance, i.e., locating the controls so that the specific user can achieve near optimal performance given their capabilities. Fit described in this way directly influences human performance. Therefore, within our models, we may use fitness to modify user performance, or we may place design constraints which assure a minimum level of performance for a specified group of individuals, where the specification of this group recognizes differences between individuals. Thus, the specification of this group falls within the Personnel domain, with excessive constraints limiting the available personnel and thus the ability to provide a level of manning sufficient to achieve the desired manning level, i.e., the manpower, for the system. Regardless of the point of view applied, improvements in human performance will generally improve system performance. Placing fit in the context of the system, increasing fit will likely require the size of enclosures to be increased to accommodate human reach and access, increasing, for example, aircraft volume and weight, which negatively affects system performance.

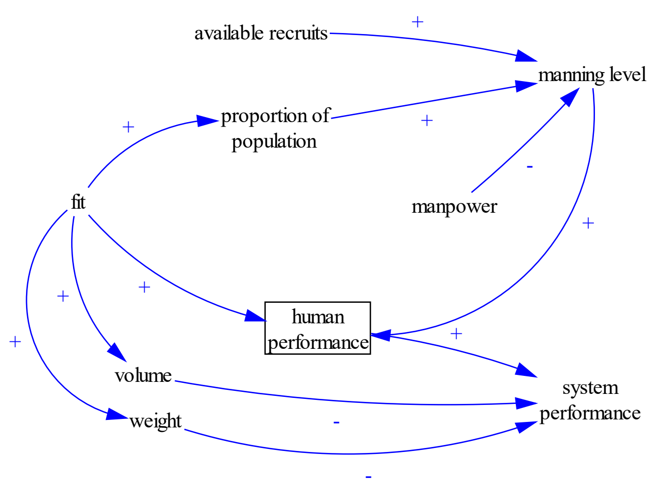

Figure 10. Causal loop diagram illustrating the influence of fit one potential influence on system performance.

2.3.4 Metrics of Acute and Chronic Injury

The final system metric which needs to be discussed is the impact of the system on the human, such that it results in either acute or chronic injury. Acute injury refers to harm that occurs in a short amount of time or an illness that goes away quickly (i.e., falling and breaking a wrist, sunburn, or a short illness like the flu). On the other hand, chronic injury refers to any disease or illness that lasts for a long time or is a result of long-term exposure (i.e., cancer, black lung, hearing loss, long-term back or shoulder pain) (Brown & Rzucidlo, 2011; Flint et al., 2014). In this paper, we are primarily interested in avoiding injury rather than recovery. Thus, we will refer to acute injury as injury which occurs in a short period of time (i.e., less than 1 week) and chronic injury as injury which occurs over a protracted period. These effects are often characterized by their probability of occurrence and severity, termed risk (Blunt et al., 2011; Cabeças, 2015). These risks occur due to the exchange of energy, material or information from the system or environment with the human or from the spatial interfaces between the human and the system. Although these categories are similar to those we used when describing fitness, their application is markedly different. For fitness, we are discussing aspects of the system where the human is intended to interact with the system. However, injury can occur either at these designed interface points between a human and a system or through unintended points of interaction.

Energy typically includes different wavelengths of electromagnetic energy (i.e., light, sound, or gamma radiation) through air or physical energy transfer (i.e., g-forces, vibration, or impulse forces). Energy sources of concern also include thermal radiation and electrical energy which carry varying degrees of risk (Cabeças, 2015). Material transfer includes the exposure of the body to hazardous chemical or biological materials via ingestion and the gastrointestinal tract, inhalation into the airways, or direct skin absorption (Cabeças, 2015; Jahn et al., 2015). Information may include witnessing traumatic events or experiencing extreme stress which result in psychological harm (Cabeças, 2015; Oakman et al., 2018). Information can also include knowledge that a worker assimilates about the workplace culture and management styles, as well as the perceived value that an employer places on each employee and their individual safety (Oakman et al., 2018). This information may alter one's willingness to participate as an effective member of the larger team or result in a degraded mental state. Other sources of acute or chronic injury may come from the way that the human interacts with the system. Repetitive motion, possibly combined with significant force (i.e., heavy lifting, repetitive tightening of bolts) or static workspaces (i.e., seated office work) may result in long-term ergonomic injuries (Cabeças, 2015; Jahn et al., 2015; Oakman et al., 2018). Additionally, system irregularities or human actions (i.e., spilled liquids, cluttered walkways) may cause instances where slips, trips, and fall-type accidents, result in acute injury.

Figure 11 displays examples of the types of health conditions that occur from the exchange of material, energy, and information between the human and the system, as well as the spatial relationships between the human and the system. An example of a chronic health condition as well as an injury is shown for each category. For instance, an exchange of energy in the form of repeated loud noise over a lifetime may result in the chronic condition of hearing loss, while a short exchange of energy in the form of UV-radiation may result in a radiation burn to the skin. Similarly, a short-term exchange of hydrochloric acid may result in skin corrosion and a chemical burn. On the other hand, long-term inhalation of coal dust can result in permanent damage to the lungs and black lung disease. Information that a person is exposed to during the use of a system may have short term effects, causing anxiety around using the system (for instance a new worker hears of a previous accident in which an employee lost their arm in the industrial shredder, which causes anxiety while using the shredder). Repeated stress in the course of work may result in post-traumatic stress disorder. Finally, the human interfaces with the system may result in injury due to slips, trips, or falls in the short-term, or the repeated use of a system (i.e., computer system) may result in musculoskeletal issues, such as carpal tunnel.

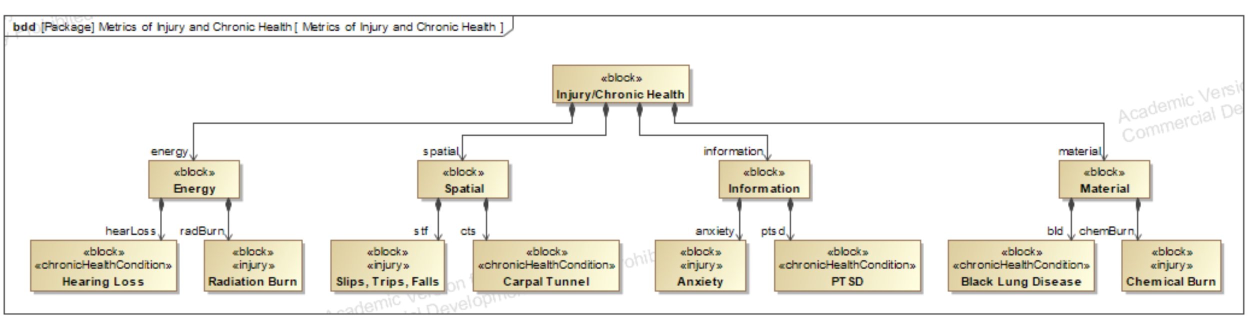

Figure 11. Depiction of categories of acute and chronic health injuries with examples.

During system design, traditional safety analysis is often concerned with managing acute injury, where the cause and effect are directly observable, while occupational health is likely to focus on reducing or managing chronic injury where the temporal delay between exposure to the injury inducing stimulus and the manifestation of observable injury obfuscates this causal relationship. It can also be noted that control strategies for these injuries can also be classified. For example, Figure 12 depicts a taxonomy of typical control strategies (Roberts, 2003).

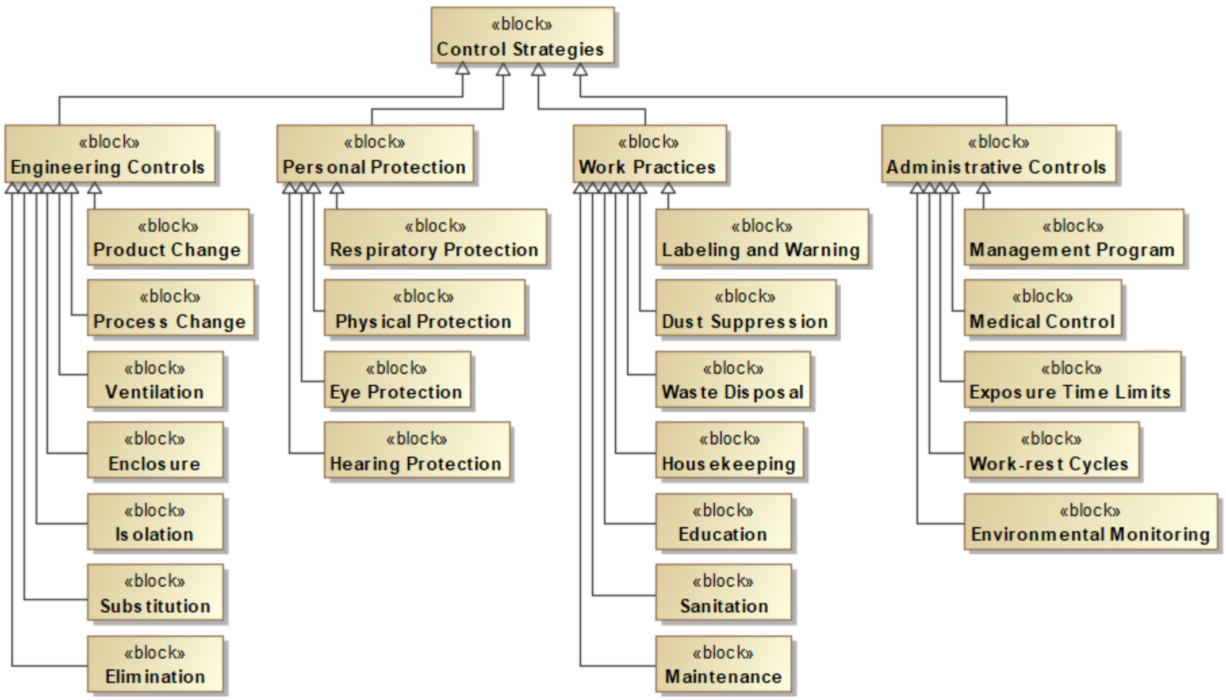

Figure 12. Control Strategies to Eliminate or Control System Hazards

Within the occupational health community there is a hierarchy of controls that are used to eliminate risk and exposure to hazards for workers. Within this hierarchy, the controls at the top of the hierarchy are considered the most likely to be effective at protecting workers, while those at the bottom of the hierarchy are considered less protective or effective, in part because they rely on individual workers actions (Manuele, 2014). This hierarchy is widely recognized in the occupational health community and recommended by standards and regulatory organizations such as ANSI, OSHA, and NIOSH. The number of tiers in the hierarchy may vary based on how an organization wishes to group different strategies, but five to six steps are commonly used (Lyon & Popov, 2019). These are: Elimination, Substitution, Engineering controls, Warnings, Administrative controls, and Personal protective equipment (Lyon & Popov, 2019; Manuele, 2014). If one step is to be eliminated, it is Warnings, which are then grouped underneath administrative controls, as in the OSHA and NIOSH hierarchies (NIOSH & CDC, 2015). The process undertaken to implement the hierarchy of controls is shown in Figure 13. The reasoning behind these hierarchies is that removing a hazard from the worker's environment is the best way to reduce risk of acute injury or chronic health effects. This is done by designing or re-designing the process to eliminate the source of the hazard or substituting the

DISTRO A: Approved for Public Release; Distribution Unlimited hazard for a less hazardous alternative. In many cases, these steps may be impossible to implement due to cost or process restrictions. Engineering controls are used to isolate the hazard, and include solutions such as enclosing the equipment, providing ventilation, or installing interlocks (Lyon & Popov, 2019; NIOSH & CDC, 2015). Warnings are used to alert individuals of the presence of hazards visually or audibly. Warnings are implemented through signs, auditory alarms, and labels (Lyon & Popov, 2019). Administrative controls are work practices and procedures that indicate how a task is to be done so that it is completed in a safe manner to reduce worker exposure. These controls may include procedures like job rotation or break schedules. Personal protective equipment (PPE) is generally considered the cheapest and easiest to implement, but this is at the potential cost of worker safety and productivity (Lyon & Popov, 2019; Manuele, 2014; NIOSH & CDC, 2015). This is because it does not remove a hazard or risk from the environment, but instead relies on individual workers to use the PPE as intended in every instance. PPE includes safety glasses, hearing protection, and gloves, among other options which must be donned and doffed and that can interfere with work activities.

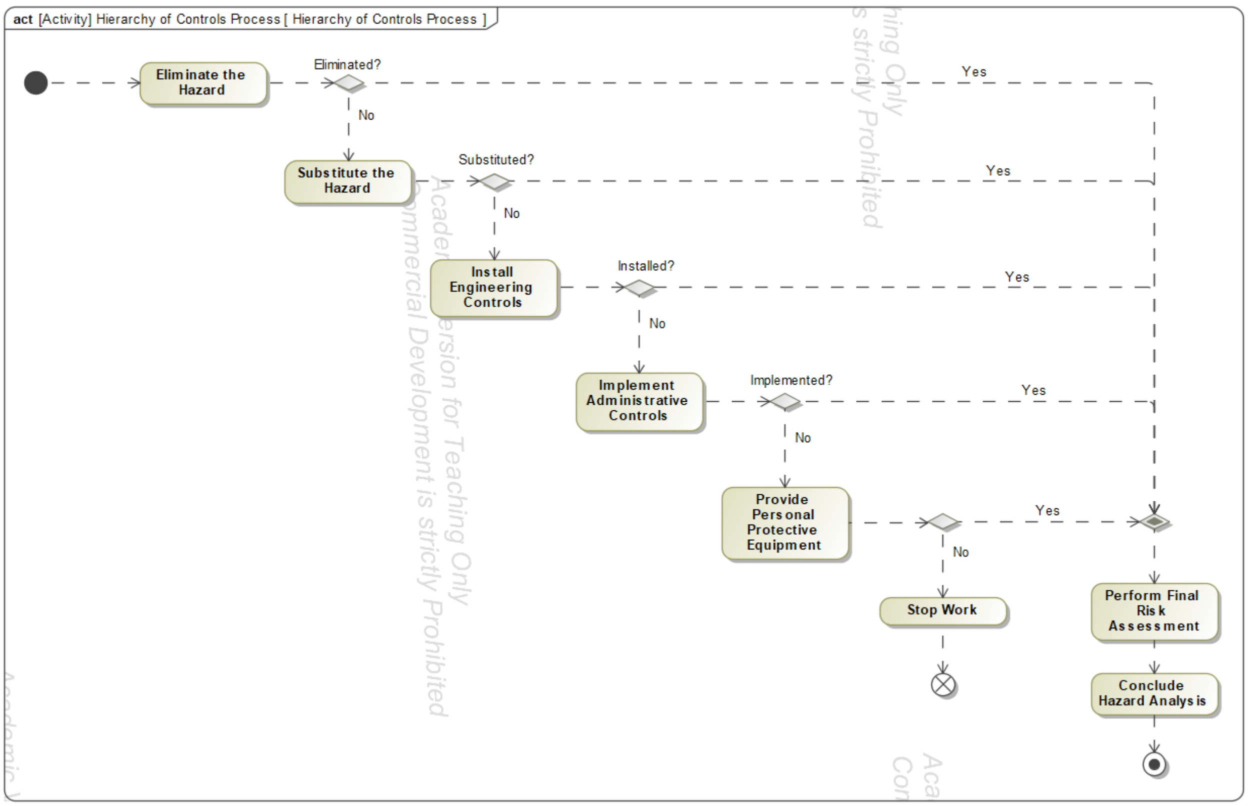

Figure 13. Depiction of the Process to Implement the Hierarchy of Controls (Roland & Moriarty, 1983)

During system design, it is important to not only model the existence of potential hazards and their associated risk but to document expected control strategies and the effect these may have upon system performance. As an example, a maintenance activity might result in airborne material which presents a hazard when inhaled or absorbed through the skin. The control method might be to require donning and doffing hazardous material suits. The procedural steps of donning and doffing these suits will then impose additional tasks on the maintainer. Further, they may increase the likelihood of heat exhaustion or heat stroke, which further requires more frequent rest breaks, further increasing the frequency of donning and doffing the PPE. These steps have the potential to reduce the effectiveness of a maintainer, which will need to be compensated for by increasing manpower which increases system lifecycle costs.

2.3.5 Metrics of Human State

As discussed earlier, human performance, fitness, and perhaps to some degree injury are affected by human state. In discussing measures of human state, the goal is to understand measures which likely influence human performance or fitness measures provided in the previous section. In the cognitive domain, common state measures include items such as:

- Workload or Available Mental Capacity
- Situation Awareness
- Alertness Level
- Fatigue Level
- Stress Level
- Vigilance Level
- Motivation Level
- Depression or other Mental States which Affect Motivation Level

Although these states may well influence human cognitive performance and significant research has been conducted to understand many of these items, perhaps the best understood among these are workload, situation awareness, alertness, and fatigue. Methods for modeling workload, alertness, and fatigue, as well as methods for modeling the effects of these states on human performance are present in the literature. The remaining metrics are approached from an observational point of view within the Human Factors literature, although there has been a large amount of research conducted to understand the influence of Situation Awareness and Vigilance on performance even if methods to predict these states are often absent or are not well integrated within the existing literature.

Physical human states are perhaps easier to quantify. Important states might include the level of injury or might include some modification of human attributes related to fitness by the inclusion of auxiliary devices, such as PPE. For example, a human's auditory, visual, small motor skills may all be modified when wearing a Mission Oriented Protective Posture (MOPP) suit as the head covering blurs vision, reduces sound transmission to the ear and adds gloves which reduce manual dexterity of the hand. In another example, body armor adds weight to the upper torso which affects one's ability to lift other weight. Thus, while models such as lifting standards might be used to understand the ability of a human to safely lift a certain mass, inclusion of body armor will reduce the amount of weight that can be safely lifted. Understanding the effect of these physical states on fitness and performance will also be important.

It is also important that many of the human states are also related to human readiness. Lack of alertness, extreme fatigue, stress, or loss of vigilance may all significantly reduce performance as will physical injuries. These states can reduce the effectiveness of individual soldiers to unacceptable levels, significantly increasing the likelihood of mission failure.

2.3.6 Behavioral Models

When discussing human performance, it is often necessary to prescribe the task sequences we envision an individual performing to accomplish a function or goal. As indicated earlier, this behavior is often predicated on task-based models which are modified based on constraints which are imposed by the human, system, or environment (Anderson et al., 2004; M. E. Watson et al., 2017). However, humans often adapt their behavior to accomplish goals (Card et al., 1983; Geddes, 1989) and this adaptation can be motivated by circumstances which sometimes cannot be foreseen during system design (Cox & Szajnfarber, 2017). Therefore, it is likely necessary to model methods to accomplish each goal we expect the human to pursue. Further, we likely need to model numerous task sequences which we know may be employed to accomplish each goal and select among these methods for accomplishing the goals based upon human, system, or environmental state. Such an approach, coupled with models of human task time variability, may permit us to include some range of human task variability within our models.

Once a system has been fielded, traditional methods such as task analysis or cognitive task analysis may be used to analyze the work that the operators perform to update the task-based models. It may also be important as we talk about human digital twins to provide mechanisms which permit the model to observe human behavior and to automatically understand and construct task-based descriptions of human behavior based upon these observations. While such a mechanism may require significant research to develop, this knowledge permits improved models of human behavior to be constructed based upon real world observation. Thus, these system models may not only include prescriptive models of human system interaction in which the humans perform task as envisioned by the system designers but descriptive models which consider adaptations to these processes which the operators employ as they "learn by doing" as they apply the system within their environment.

2.4 Defining Human Viewpoints and Views for System Models

In this paper we will apply the term, "viewpoint" as a set of conventions that define how a "view" is constructed (Yamada, 2009). A "view" depicts the system from a particular perspective to provide information to support decision making by a particular stakeholder (Bruseberg, 2008; Orellana & Madni, 2017; Yamada, 2009). Visualization of views may be graphical (i.e., diagrams), tabular, matrix, or textual (Bruseberg, 2008). Most existing modeling methods do not specify how information should be represented, only the kind of information to be presented.

Various views have been discussed within the human-centered literature. Perhaps the broadest views provided have included humans in views intended to capture system architecture, referred to as Human Views (Bruseberg, 2008; Handley & Knapp, 2014). These views are shown in Figure 14. As shown these views include a description of the organization in which the system will be employed (HV-D). As an example, this may include a squadron and support functions for an aircraft. Related to this is the individuals available to fulfill each role within the organization (HV-A). The roles played by each individual in the organization and the competencies they require to perform effectively are also provided (HV-F). These competencies can be linked to the functions and tasks that each individual is expected to perform where these functions and tasks are shown in HV-E. Related to this is the structure of interaction among individuals within the organization and the technical components they employ (HV-C). The dynamic drivers of human performance can also be documented (HV-G) as well as the objectives and metrics of performance for the organization (HV-B). Each of these viewpoints are important and can be necessary to define to understand the performance of the system.

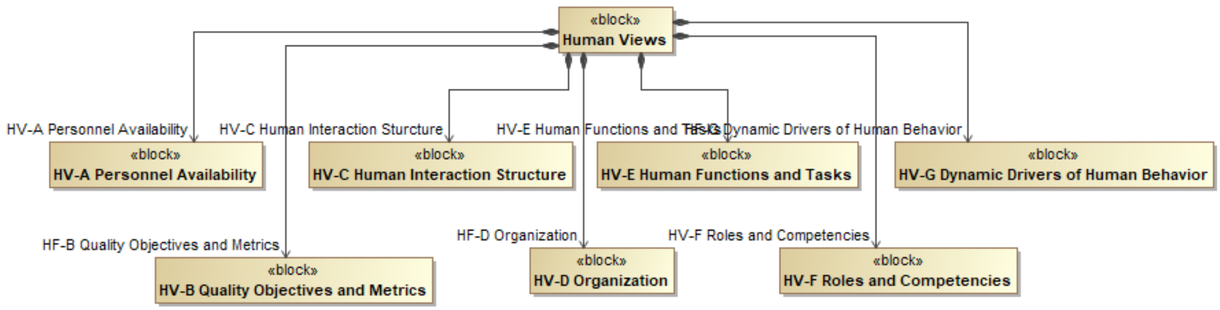

Figure 14. Human Views as described by Bruseberg.

Other views have been discussed which capture basic human performance measures and human workload to address human factors engineering concerns (Carlson et al., 2019; Liaghati et al., 2020; Stanton et al., 2021; M. Watson et al., 2017; M. E. Watson et al., 2017). Finally, the systems engineering literature discusses the fact that views showing satisfaction of stakeholder and system requirements; system performance, system effectiveness, life cycle cost, and stakeholder value are important in trade-off analysis, especially if they support quantification of uncertainty and visualization of the trade-space (Parnell et al., 2021).

While each of the approaches provide viewpoints which may be useful during system design, they do not provide a structured approach to suggesting a comprehensive family of viewpoints. Perhaps one approach towards developing a comprehensive family of viewpoints which are relevant to humans during system design is to begin with Human Systems Integration policy. Department of Defense 5000.02 provides guidance to the program manager of an acquisition program which directs the program manager to "optimize total system performance and total ownership costs, while ensuring that the system is designed, operated, and maintained consistent with mission requirements.

To provide viewpoints which can be effectively modeled within MBSE, a method to model each viewpoint is necessary which provides enough detail to enable one to replicate the viewpoint. Further, the elements of the viewpoint and their relationships must be provided and defined. Additional research and development are likely necessary to determine the best views for modeling various aspects of these systems. This exercise is left to future development of the style guide.

3 Issues in Human Modeling

Throughout this paper we have alluded to multiple issues in human modeling. However, it is worth summarizing at least a few of these issues. First, it is important that we can model some aspects of humans for a lot of reasons, including creation of medical interventions, improvement of training, and understanding or improving system design. It is important that this paper has focused on the later goal. As such, we need to model the effects the human has on system performance and the points of interaction, intended or not, between humans and these systems.

It is important that the person interacts with the system in an environment which can contain humans outside the system, including intelligent adversaries. On the other hand, there are times that modeling the interaction of a single person with a single interface within the system can have significant value in understanding how to model the system. As a result, we can model the system at various levels of abstraction which ranges from the influence of the system on a single human attribute at a low level of abstraction, e.g., likelihood and severity of neck injury, through wargaming models where we might investigate the effect of even this same attribute on a mission effect, such as probability of kill in air-to-air combat. Notably at the low level, it is only necessary to model the interface and interaction between a single human and the system. At the high level, it is necessary to model the interface between multiple large organizations of humans. Going forward, it will be important to develop a modeling framework to describe the appropriate levels of abstraction for model construction and to understand methods to integrate models across these levels of abstraction.

It is also important that while metrics such as likelihood and severity of neck injury may be a low-level metric from a system design viewpoint, these are relatively high-level metrics from the human modeling point of view. Afterall, these metrics are influenced by the forces and moments the neck experiences at different periods of time, fatigue of the neck muscles which might be quantified through metrics such as blood oxygen levels within these muscles, and even prior nutritional and genetic factors which influence the development of the neck structure. Development of model frameworks which provide guidelines for discussing and designing appropriate models at each level of abstraction are necessary to permit the seamless integration between human and system models.

Important in integrating these models is the development of appropriate metrics. In this paper, we focused on the development of a taxonomy of metrics that should be useful during system acquisition. However, this paper focused on a level of abstraction that is somewhere between the low and high levels of abstraction from the previous paragraph. There are likely to be multiple additional metrics that will be useful at other levels of abstraction. As we define the different levels of abstraction to model, it will be necessary to understand how metrics computed at one level of abstraction support or are combined into metrics at higher levels of abstraction. It is important to realize that some metrics will be weighed as more important to the stakeholders than others and that some stakeholders will not understand some of the interactions between these metrics. For example, a stakeholder might not be concerned that a particular interface design for a maintainer adds some number of minutes to a maintenance activity. Afterall, the organization may have slack time available so that these minutes do not actually impact important system or mission level metrics and, if not, additional maintainers can be introduced into the maintenance activity to create the slack necessary to compensate for this increased time. However, eliminating slack time often reduces the resilience of the organization and increasing personnel increases lifecycle costs as well as increases pressure on the recruiting and training pipeline. It is possible that these effects may be important to the stakeholder but only if they are aware of these secondary influences. Therefore, it is important that the metrics that are chosen are not only relevant to showing differences between different design alternatives but are also interpretable and valued by decision makers.

The various human models are at different levels of development. While models of human perceptual and physical processes are evolving, these models are much more robust than existing cognitive models. Further, while cognitive models for individuals are still in relatively early stages of development, models of team or organizational behavior are more nascent. Further, these later models are influenced by large numbers of interacting external factors which are difficult to quantify and the cognitive processes which must be modeled to create effective cognitive and team behavior models are often opaque, making development of comprehensive models in this area extremely difficult. Additionally, the interactions between even relatively well understood human perceptual and physical processes are often not well understood and remain an area of further development. One method of modeling human and teaming behavior has been task-based models where we model the tasks that humans perform when interacting with a system to understand human and system performance. While these models are useful in many domains, they suffer from their inability to adapt to real world constraints. Therefore, these models are unable to correctly model human behavior over time as humans innovate new ways to deploy systems and tools through modification of the tasks and task sequences they employ. A compelling attribute of the human digital twin architectures is this real-time collection and analysis of data provides insight into areas where the models do not predict real-world behavior and perhaps this will provide insight into human adaptations within these systems.

The human digital twin systems are also important to consider as these architectures provide mechanisms to obtain real world data which can be used to support model development and assessment. However, as shown in these architectures, data collection to support modeling must include information about the human, the systems they are employing and their environment. Often data standards do not exist which permit the collection of appropriate data in our real-world systems to facilitate these models as it really requires us to gather data across the SOS that the human interacts with. As we discuss open systems architectures, it is important to architect data standards which provide robust information to support human modeling. Often this data may exist within systems but are not accessible or stored across the SoS (Saunders, 2005). Recent work by Schneider and colleagues sought to extract data from existing interface and simulation workstations to support building human models (Schneider et al., 2022). However, this exercise, which was conducted with a system that was designed to support data collection, illustrated the difficulty of storing and merging real world data when portions of this data are updated in real time while other important elements are updated at slower clock rates and still other data elements are driven by environmental, system or human events which trigger state changes in one of these elements. Further, to support human digital twin development systems must be engineered to make this data open and available to construct these models. Standardized data formats may need to be developed in this area which extend beyond today's data interchange formats.

These models must also appropriately recognize the differences both between individuals and changes in individual differences which occur with time. The differences within individuals can include a variety of factors, including fatigue, stress, workload, injury, and many others. Differences exist between individuals due to differences in their physical or mental capacities, training, emotional IQ etc. Today many of our human models attempt to predict mean performance but do not adequately consider the differences between individuals or the variability in human performance over time. Further development of methods to include these factors in models are necessary.

Many of the existing human models model the effects of system or environmental factors on a single human metric. However, these models often do not consider that changes in one of these human metrics often influence changes in other human metrics through interactions. Further effort is required to understand how to compose more complex human models from less complex single metric functions.

Finally, it is important to understand that each of the models were built for a purpose. Some of these models have been verified or validated for that purpose but more uniform and robust methods for verifying and validating the models for this purpose are required. Further, it is desirable to apply many of these models for alternate purposes. We need to develop specific guidelines on how to extend verification and validation to alternate purposes. Further, it will be necessary to develop accreditation methods which provide assurance that the models provide enhanced or adequate prediction of real-world events (*Department of Defense Standard Practice Documentation of Verification , Validation , and Accreditation for Models and Simulations*, 2012). This discussion of assurance will need to address the question of whether it is necessary for human models to augment system models to provide truly realistic metric estimates or is it only important that the addition of human models provide an increase in the model's prediction of real-world events compared to models that do not incorporate human models. Overall, these goals need to be agreed upon and understood before modeling efforts are undertaken.

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5 Glossary

Accreditation – certification that a model, simulation, or federation of models and simulations with associated data are acceptable to use of a particular purpose.

Acquisition - a process for acquiring systems, usually from one or more external organizations.

Acute Injury –injury which occurs in a short period of time (i.e., less than 1 week), usually due to a single exposure to a hazardous condition.

Alertness – the state of active attention.

Architecture – the conceptual model that defines the structure, behavior and other views of a system which is organized in a way that supports reasoning about the structures and behavior of a system.

Chronic Injury – injury which occurs over a protracted period typically due to repeated exposure to a hazardous substance or work condition.

Cognitive Task Analysis – a method for collecting, analyzing and communicating the cognitive or mental processes and events executed by one or more individuals while performing an activity.

Digital Acquisition – the application of digital models and databases to the acquisition of systems.

Digital Entity – a digital representation of the real-world system, typically including a database for warehousing the sensed information and a model. The model will often contain both mathematical models based on first principles and statistical models capable of explaining variability of the data.

Digital Engineering – the application of digital models and databases to the design, development, and assessment of engineered systems.

Digital Twin – pairings of a real-world entity and a digital representation of the real-world entity which includes a model of one or more attributes of the real-world system where the pair of entities are linked such that a change in the real-world entity or its digital representation produces change(s) in the other.

Digital Human – a representation of the structure or behavior of a human in a model.

Discrete Event Simulation – a model which decompose the operation of a system into a sequence of events which can be executed to determine the performance of the system.

Fatigue – a state of tiredness that is often associated with excessive or prolonged activity. It is often associated with the buildup of by products, such as lactic acid or saratonin, formed during activity.

Interchange Component – a data transfer system which permits a one of the entities in the digital twin to be updated in response to changes in the other entity.

Human Digital Twin - a pairing of a real-world human and a digital representation of human which includes a model of physical, physiological, personality, perception, cognitive performance, emotion, or ethics of a human; where the human and its digital representation are linked such that a change in the real-world human or its digital representation produces change(s) in the other.

Human Factors Engineering – application of human factors information to the design of tools, machines, systems, tasks, jobs and environments for safe, comfortable and effective human use.

Human Systems Integration – integration of the domains of manpower, personnel capability, human factors engineering, training, Soldier safety, health hazards prevention and Soldier survivability to manage the impact of these domains on system design.

“ilities” - emergent properties of a system which have value to the stakeholders and generally permit one to represent performance of the system across a wide range of contexts.

Integration - method or process that unifies the product and process components into a whole in a way that ensures hardware, software, and human system components will interact to achieve the system purpose or satisfy the customer’s need.

Functional Goal – a set or state of achievement intended by one or more agents.

Logistics – the management of the flow of things between the point of origin and the point of consumption to meet stakeholder requirements.

Mental Capacity - the mental resources an operator can employ towards the completion of tasks within permissible time limits

MBSE - Model Based Systems Engineering

Model Based Systems Engineering – the formalized application of modeling to support system requirements elicitation, design analysis, verification and validation activities throughout the system lifecycle.

Motivation – reasons living animate entities initiate, continue, or terminate behavior at a given time.

Perceptual Loop – a model of human goal-seeking behavior often characterized by a repeated multistage process including sensing, perceiving, decision-making and action.

Real-world -the environment in which a physical system or human resides and performs activity.

Real-world Entity – either or a combination of one or more humans and machines which are instrumented with sensors to sense the state of the environment, the human or the machine.

Real-world Human – a physical human being.

Real-world System – a physical, man-made system intended to aid a human in performing work.

Prediction Engine – a processor and embedded model which facilitates the forecast of a future event or data.

Situation Awareness – the perception of environmental and system elements and events with respect to time or space, the comprehension of their meaning, and the projection of their future status.

Stress – an organism's response to external forces such as an environmental condition.

Sustainment – a concept of logistics and military acquisition wherein a system or organization is maintained in a state of preparedness.

System Lifecycle – all phases of a system to include conception, design and development, production, distribution, operation, maintenance and support, retirement, phase-out and disposal.

System Model – a mathematical or logical representation of a system and its embedded processes.

Task Analysis – a process for determining, analyzing, and communicating the manual and mental activities which are required for one or more people to perform a given task. This analysis often includes task and element durations, task frequency, task allocation, task complexity, environmental conditions, necessary clothing, and equipment.

Taxonomy – a scheme of classification in which things are organized into typically hierarchies of groups or types.

Validation – process for determining the degree to which a model, simulation, or federation of models and simulation with their associated data accurately represents the real world from the perspective of the model's intended use.

Verification – process of determining that a model, simulation, or federation of model and simulation implementations with their associated data accurately represents the developer's conceptual description and specification.

Vigilance - the ability to maintain attention and alertness over prolonged periods of time while monitoring for rare stimuli among frequently occurring stimuli, is required. Usually quantified using a vigilance decrement, i.e., the loss of performance as a function of task performance time.

Virtual – a representation which is intended to provide the impression of the item being represented. For example, when experiencing a virtual world, an individual is intended to believe they are in the represented virtual world even though they exist in a different, real world.

Workload – the cognitive or physical effort perceived by a user during execution of an activity, sometimes quantified in terms of a proportion of the user's maximum capacity.

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14. ABSTRACT
System models are being applied to aid the design, specification, acquisition, operations and sustainment of systems. Within these phases of the system life cycle, these models may be embedded within digital twins to aid system improvement. This report explores the state of the art for including humans within within system models and digital twins. The report is intended to provide some common language and definitions, to provide some vision for the application of human digital twins, and discuss the modeling of humans within system models to support system design and acquisition.

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