Effective Variety? For Whom (Or What)?

A Folk Theory on Interface Complexity and Situation Awareness

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***Abstract*— Complexity is concept that is typically used to describe the size or composition of a system and its constituent components. The cybernetics community has long recognized the need for complexity, understanding that only the variety of a system can destroy the variety of the environment and inputs to the system. Conversely, the applied psychology and decision making communities generally acknowledge that increased complexity degrades decision making performance in dynamic tasks through several mechanisms. A notional model of "Effective Variety" is discussed, which states that there is an optimal level or range of complexity for any human-machine interface that will facilitate optimal dynamic decision making performance in a human-machine team. This initial paper discusses a concept and model of Effective Variety, and focuses specifically on how interface complexity affects Situation Awareness (an antecedent to decision making performance), and areas for future research into such a theory.**

Keywords—Complexity; Situation Awareness; Requisite Variety; Dynamic Decision Making; Human-Machine Interface

I. Introduction

In the era of highly-networked and service-oriented systems where data are being made available faster than we can use them, complex and adaptive systems are increasingly prevalent in lieu of simpler solutions to achieve our goals [1]. Regarding the design of these systems, one may ask the question:

How much complexity is the right amount of complexity?

Research in the fields of cybernetics and computer science has shown that adaptation, resilience, and representational fidelity of the environment (all positive characteristics) are associated with an increased level of complexity in a system. From this system-centric viewpoint, the answer is likely to be some version of "as complex as it needs to be." Research in the fields of human factors and decision making has shown that complexity of systems (namely their Human-Machine Interface (HMI)) generally degrades performance in dynamic decision making tasks. From this point of view, parsimony is key and the answer may be "as simple as possible."

This paper makes an incipient effort to answer this question, while exploring and fusing research from two related fields. The intent is to develop a notional model and viewpoint on complexity that accounts for performance of both the human and the system. "Effective Variety" is not a new concept unto itself, but merely a name being ascribed to a phenomenon that has been referred to by many different names (or often no name at all) throughout the literature. It is hoped that by defining and explaining the many component theories underlying the concept of Effective Variety, that it may spur on dialogue and research towards finding calibrated levels of interface complexity for increased performance in human-machine teams across different contexts.

II. Complexity and The Law of Requisite Variety

In general, complexity is somewhat of a blanket concept that has been used to describe a number of phenomena across a wide variety of disciplines [2]. Because they are so similar in form and function, and because complexity is so broadly defined, complexity and variety are used interchangeably throughout this paper. The following sections will define and discuss the effects of complexity in human-machine interfaces (which may be graphical, text-based, physical controls, or otherwise) on Situation Awareness (SA) and decision making.

A. (An Attempt at)Defining Complexity

Before delving into the cases for and against complexity in system design and decision making, one must first attempt to define the concept. While definitions vary and the application of the term is diverse across the literature, most definitions of complexity in the social sciences include a measure of size (number of components), interconnectedness of components (number of connections), and dependencies or causal relationships governing the connections among components [2, 3, 4]. Any number of these elements are used to describe a "complex" condition in an experiment on decision making [4, 5].

Reference [4] further refined complexity by breaking it into two types: Structural and Dynamical. Structural complexity is defined as many of the aforementioned features, such as size, diversity, and interdependence of components. Dynamical complexity refers to the degree of nonlinear change in the system as processes are executed. Therefore, complexity should not only consider a static picture of a system's structure, but should also consider how that structure behaves and changes over time while interacting with the environment (which includes the human element). Reference [6] echoed this characteristic of complexity when assessing medical decision making for patients, whose conditions change continuously over time because of a variety of factors. While assessing human-machine teams, complexity can be found in a variety of sources, including the environment in which the decision making task is taking place, and the nature of the job or task itself.

There are many definitions and measures of complexity in the cybernetics and computer science domains, and they are continuously growing. In Shannon's Information Theory and its derivatives, information is measured in "bits" and is associated with the removal of uncertainty as information is provided [7]. Reference [8] lists dozens of potential measures of complexity, but highlights their commonalities in that they all are used to answer one of three common questions regarding a system:

- How hard is it to describe?
- How hard is it to create?
- What is its degree of organization?

It can be seen without undue effort that the definitions of complexity across the cybernetics and social sciences communities readily map to each other. The structural complexity (quantity, diversity, interconnectedness) and dynamical complexity (how the components behave over time) are common elements when used to describe complex systems in either field.

B. *Requisite Variety and the Case for Complexity*

Ashby's Law of Requisite Variety has long been used to demonstrate the need for system complexity by stating that only variety can destroy variety [9, 10]. Based on information theory and rooted in the field of cybernetics, requisite variety simply states that the degree to which one can control a system is the proportion of complexity in the controls to the complexity in the system itself. By applying the law of requisite variety at each concurrent layer, one can see that a system must be as complex as the environment and the task set it will perform in. Additionally, the interface between the human and system must have requisite variety that is on par with the complexity of the system itself so that the human can effectively control the system. Therefore, interface complexity is driven by system complexity, which is driven by environment and task complexity - where each dependency is defined by Ashby's Law.

A look at the human immune system illustrates this concept. Because of the variety of antigens the immune system faces (environment and task complexity), it does not simply rely on having an antibody on hand for every known antigen. Instead, antibodies adapt as needed to combat different antigens while maintaining a sense of coherence [11]. That is, the complexity of our antibody capabilities are in comparison to the complexity of possible antigens is the degree of control we have to fend off external perturbations to our systems. In a more relevant use case, the use of simplistic, reductionist tools and decision aids in the Intelligence Community are rejected by analysts because they create overhead in assessing probabilities and numerical values, but do not handle the complexities of meaningful intelligence work (i.e., they are brittle to the complexity in the environment and the task itself) [12, 13].

Furthermore, system complexity offers advantages to human decision makers, namely by imparting contextual information that is valuable for enhancing comprehension of information, and which may be a source of cues for decision makers with relevant domain expertise. As [2] points out, there are multiple components to any message in addition to the informational component (the literal information value of the message). Additional components include the symbolic value of the message (e.g. an immediate or delayed response) and emotional values of messages, which play a large part in analysis of communications. This was demonstrated recently in a text analysis study where there was no statistical significance when responses were reduced to numbers, but there were several significant findings when the full complexity of messages was considered [14]. In a medical care scenario the application of simple rules to complex scenarios degraded the advantages of expertise (such as cue and pattern recognition), and made the treatments brittle to changing information [6].

The following assertions can be made with respect to complexity and system performance:

- The higher complexity of a system in comparison to the complexity of the environment, the higher control that system exerts [9].
- The more adaptive or resilient a system is, the more complexity it must have [11].
- Complexity (specifically the quantity of information) increases knowledge and decreases ignorance [15].

III. Situation Awareness and Decision making

Having defined and explored the merits of complexity in system design (e.g. engenders adaptability and representation of context), one must also consider the effects of complexity on human decision making performance. There is a considerable amount of literature that shows how complexity can degrade decision making performance through a variety of mechanisms, namely by decreasing SA.

A. *Situation Awareness*

SA is a construct that describes how different factors in complex, dynamic systems affect a human's ability to acquire and interpret information for effective decision making [16]. SA is a diagnostic of a state in a dynamic world that provides a ground truth to assess (i.e., whether the world is perceived accurately or not), which is contrasted against using decisions themselves as diagnostics (i.e., some choices are "more right" than others) [17].

The SA model is composed of three levels of SA, which are briefly described here [16]:

- *Level 1 SA: Perception of Elements in the Environment (SA_1)*. The first level of SA involves perceiving the status, attributes, and dynamics of relevant elements in the environment.

- *Level 2 SA: Comprehension of the Current Situation (SA_2)*. The second level of SA goes beyond awareness of elements, and includes understanding the significance of those elements with respect to operator goals. While a novice and expert may have the same SA_1 given a set of elements, the expert would likely have greater SA_2 than the novice.

- *Level 3 SA: Projection of Future Status (SA_3)*. The final level of SA involves comparing the comprehending meaning of the perceived information with operator goals to predict projected future states of the environment that are valuable for decision making.

It is important to note that SA is separate from, and precedes, decision making [16, 18, 5]. This also raises another important point: Higher SA does not always equate to higher decision making performance. A decision maker could have high SA at all three levels (SA_{1-3}) but no domain knowledge, and thereby make poor decisions despite their high SA. Conversely, somebody with high domain expertise but low or incomplete SA can make poor decisions. While the level of SA is not equivalent to the level of decision making performance, it is generally be asserted that higher SA enables higher decision making performance (i.e. they are positively correlated). It should also be noted that SA is context-dependent, or that it only involves the perception, comprehension, and projection of information that is relevant to achieving operator goals [16, 5]. This is an important concept because it underlies how expertise and individual differences may affect the process of achieving and maintaining SA.

B. Decision Making

Similar to the concept of complexity, decision making has many definitions attributed to it [12]. *Dynamic* decision making is different from general judgement and decision making in that it involves a series of interdependent decisions where the state of the environment changes due to external mechanics and the decision maker interacting with it over time, and where decisions are made in real time [19]. There are several classes of decision making theories, although the two most prominent classes of decision making theories are rational decision making and Naturalistic Decision Making (NDM).

The primary decision making theory in the field is expected utility theory [12]. Expected utility falls under the class of rational decision making, which describes decision making models where decisions are made to allocate a limited amount of resources to maximize an output value that is aligned with a set of goals. When faced with a complex decision space, conceptual models, or heuristics are used to reduce complexity of the problem space, so that decisions can be evaluated while considering multiple (sometimes competing) goals, risks, and uncertainty [20, 21]. In the case of rational decision making, good decision making can be defined as the achievement of the goal end state (minimizing or maximizing some output value) through commitments to certain courses of action (the decision).

NDM is the second major class of decision making theory, which focuses on how people use their experiences/expertise to make decisions in naturalistic settings in high-stakes, high-time pressure scenarios [12, 22]. The most prominent model in NDM is Klein's Recognition-Primed Decision (RPD) model, which posits that decision making is made at three levels [22], where higher levels of sensemaking are only used if necessary. When attempting to emulate this model with algorithms, they have been aptly named "Fast and Frugal" heuristics [23]. At the first ("simple match") level, the decision maker perceives a situation as "typical" and reacts with an appropriate Course of Action (COA). If the situation is atypical (but not highly complex), the decision maker must choose a COA from possible outcomes (analogs of the situation at hand). If (and only if) the situation is unfamiliar and complex, the decision maker must assess COAs via mental simulation of their outcomes. A distinguishing feature of NDM is the goal of satisficing. Rather than pursue an optimal outcome, good decision making is defined as making a satisfactory decision under time pressure.

While these different classes of theories differ substantially in their underlying models, they both can be generalized into a generic three-step scheme of decision making [12]:

- Information Acquisition
- Perception and Interpretation
- Commitment

In addition to the rationalistic and naturalistic methods just described, hybrid decision making methods can also be used in complex, dynamic environments [5]. Regardless of the method used, one can readily see the similarities in the three levels of SA and the generalized three-step scheme of decision making, especially in the first two steps. The acquisition and interpretation steps are directly affected by SA_{1-2}, while the three stages of the RPD model correspond largely to SA_{1-3}, supporting the notion that SA is critical for effective dynamic decision making, irrespective of exactly how decisions are being made. This further highlights the understanding that a decrease in SA generally results in a decrease in decision making performance [16].

IV. The Concept of Effective Variety

Having addressed the nature of complexity and how it affects both system and human performance, the initial question is revisited: How much complexity is the right amount of complexity? To attempt to answer this question with respect to dynamic decision making in human-machine teams, a concept and model of "Effective Variety" is presented (Fig. 1). It is asserted that the "right" amount of complexity for an interface lies at the intersection of the human (i.e., the decision maker) performance (blue) and system performance (red) functions. Because interface complexity is not optimal at a minimum or maximum point (like automation or trust), and that it must be calibrated appropriately based on the context of the situation (i.e. environment and task) and the abilities of the decision maker, the optimal amount of complexity is a theoretical amount that lies somewhere between the peaks of the curves. The intersection of the two functions yields the

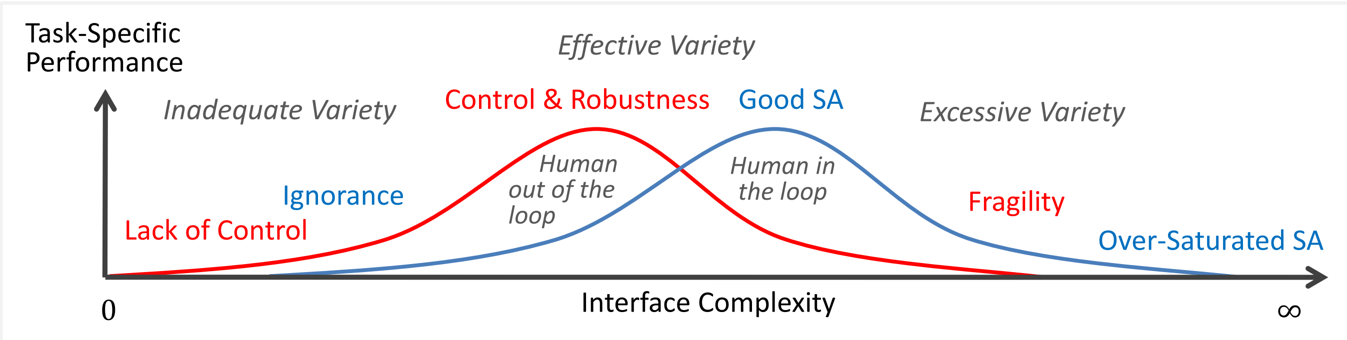

Fig. 1. Optimum interface complexity lies at the intersection of system and human performance functions (i.e. between the red and blue peaks).

highest decision making performance that is possible given both curves. However, if one assumes a cumulative relationship among the two functions, then there is a range of complexity for interface designers to consider, located between the peaks of the two functions. If there is inadequate variety, the system cannot maintain control and the decision maker is ignorant to relevant information required for the task. If there is excessive variety the system is no longer robust and instead becomes fragile [24], and the decision maker suffers from poor SA from being over-saturated with data. If there is effective variety; however, the system exhibits control and robustness, while the decision maker has good SA. The authors do not attempt to explicitly define these performance functions, but instead use approximations of normal curves, acknowledging that performance decreases with too little or too much complexity. The following sections will discuss the model itself, specifically how excess complexity degrades SA, and enumerate some testable hypotheses based on the provided model.

A. A Notional Model of Effecive Variety

Based on theories and experimental results in the literature, a notional model of Effective Variety for dynamic decision making in complex tasks and environments was developed (shown in Fig. 2). At the simplest level, complexity of the decision making task and environment drive the need for system performance (i.e.., the ability to model, represent, and be resilient to the environment and task). Requisite Variety shows that the interface must be as complex as the system to enable effective control, thereby driving up the complexity of the interface. The complexity of the interface degrades human cognitive performance, which, in tandem with system performance, directly contributes to the overall human-system performance (i.e., the ability for the human to perform effective dynamic decision making with the system at hand). Simply put, the interface should be as complex as needed for the environment and task, but no more. This high-level model is presented under the acknowledgement that there are more detailed models for each interaction shown in the model (complexity and SA is the only such relationship assessed further in this paper), and that this model is likely not exhaustive.

As previously stated, complexity has been shown to be required for system performance, specifically the system's capacity for control, resiliency/adaptability, and its ability to model or represent the environment and task to an appropriate fidelity. It has also been demonstrated that complexity is negatively correlated to human cognitive performance, which is a term used herein to describe a combination of SA and decision making. Because SA is an antecedent to effective decision making, the negative correlation between complexity and SA extends to decision making. That is, the ideal level of interface complexity lies at the point between the functions of

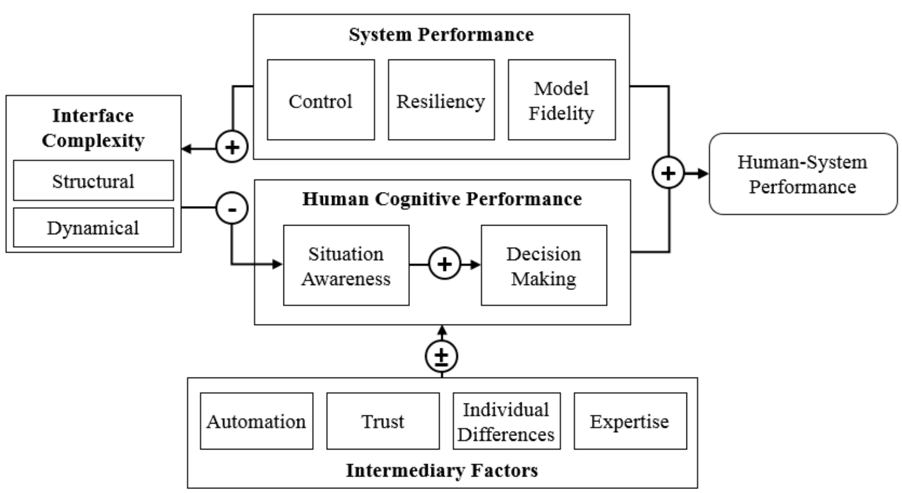

Fig. 2. High-level model of effective variety, with circles denoting how each factor drives another.

system performance and cognitive performance.

To illustrate this concept, imagine that you are exerting Command and Control (C2) over a swarm of multiple Unmanned Aerial Systems with goals to get them in different mission areas as quickly as possible while hugging the terrain to avoid detection. With an interface providing displays and controls for each system's position, altitude, and speed, you may have compromised SA and therefore exhibit poor decision making, and ultimately low human-system performance in achieving the goals. If all aircraft had a fixed altitude set slightly above the highest terrain point, SA and decision making would likely be higher because an entire dimension of (structural, and thereby dynamic) complexity was removed from the task; however, the human-system performance might still suffer because there is no control over said dimension.

The concept of Effective Variety lies in providing the right amount of interface complexity (through both displays and controls) to the human such that the human-system team has not just requisite variety (i.e. the system interface is as complex as the underlying system, environment, and tasks), but *effective* variety, in that is calibrated such that it enables effective and timely decision making. In the use case presented, this may take the form of having two or three discrete altitudes available for selection, which provides greater adaptability and representational fidelity of the environment, but vastly reduces the amount of information that must be perceived, comprehended, and projected by the decision maker.

The final component of the model is the collection of intermediary factors, which are all factors that affect cognitive performance, or the ability to "withstand higher levels of complexity" in this context. Research on Levels of Automation (LOAs) has shown there is increased performance and decreased workload when automation is used to implement "button pressing" without contributing to the cognitive aspects of the decision making process [25]. Therefore, one may notionally assert that automation mitigates complexity by both aiding in human decision making and by simply executing control tasks in a rapid manner. In addition to the role of automation in aiding decisions and performing tasks, the decision maker's trust in that automation can also affect the ability to effectively make decisions [26, 27]. Reference [16] mentions that individual differences such as executive function (e.g. attention and working memory) are factors that limit operators from acquiring SA. Finally, domain expertise allows people to manage complexity better since information is relative to how much they don't know about the states/communication prior to receiving them [15]. That is, the more one knows, the more resilient they are to incomplete SA because the potential value of information is less. Because the relationships between complexity, SA, and these intermediary factors have not been explicitly defined, they are mentioned in this model, and merit further research.

B. Complexity and Situation Awareness

While each relationship between concepts in Fig. 2 has a substantial section of the literature devoted to it, the focus of this initial paper is to specifically address how complexity affects SA. As noted by [2], there are two major types of complexity: Structural and Dynamical. Fig. 3 shows a model of how these different types of complexity affect SA, specifically from each measure of complexity to each level of SA, which is a refined view of the negative correlation between complexity and SA shown in the bottom left of Fig. 2.

Because the first level of SA is involves the perception of relevant elements in an environment, a higher quantity and diversity of components in a system will adversely affect the ability to achieve and maintain SA_1. To mitigate this phenomenon in a C2 system, filters and display layers would be provided to aid in perception of relevant entities. The second level of SA involves the comprehension of what the different perceived factors mean, therefore complexity in component interdependence would negatively affect achieving and maintaining SA_2. In C2 systems this is mitigated with features such as leader lines, which show the speed and direction in which an entity is moving, rather than decision makers needing to mentally interporlate the last few positions and their raw values. Finally, the ability to project future states (SA_3) is directly affected by the dynamical complexity of the system, or the degree to which the components change over time as they interact with the environment and themselves. In a C2 scenario, this would be mitigated by decision aids or alerts if certain projected conditions are met (such as a collision).

In addition to mapping these elements of system complexity to levels of SA, there are still relationships within the concepts of complexity and SA, respectively. One may also assert that because the dynamical complexity of a system is the

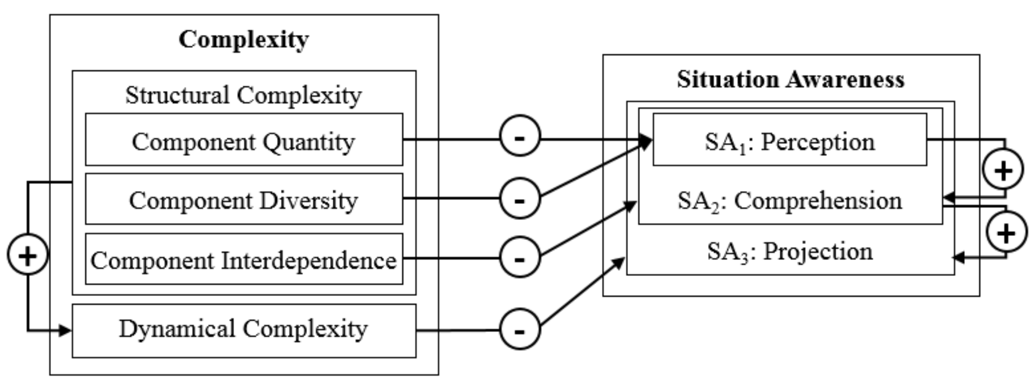

Fig. 3. Model of interface complexity and the mechanisms by which it degrades situation awareness.

complex interactions of the structure over time, that high dynamic complexity is commensurate with a high structural complexity. With regards to SA, each level builds upon the one before it in a hierarchical process [16]. This is reflected in the model, where each level of SA positively affects the one following it.

C. Some Predictions

A model has been presented based upon findings in the literature and logical conjecture. The point-by-point relationships in the model have been established by experimentation and evidence. However, no studies, to the best of the authors' knowledge, have been performed to substantiate such a model in total. Some specific, testable, hypotheses based on this model are presented towards such an effort, which are all predicated on the assumption of a dynamic decision making task of high complexity:

- With all other factors being held constant, an increase in interface complexity (from a minimal point) will result in an increase in decision making performance until an optimal point, and will then depreciate.
- With all other factors being held constant, a lower temporal pressure condition would result in higher decision making performance than a condition with a higher temporal pressure. That is, providing more time per decision would enable greater SA based on a fixed amount of complexity.

V. Discussion

A. Conclusions

This paper has outlined a concept and notional model of Effective Variety in human-machine interfaces for optimal dynamic decision making. It has been demonstrated that system complexity is generally required for higher system performance (through representativeness, robustness, etc.); however, it also deteriorates human decision making by degrading SA, an antecedent for effective dynamic decision making. Therefore, the "right amount" of system complexity falls at the point where human performance and system performance intercept (shown in Fig. 1).

Other outcomes of this research that have been presented in this paper, and conclusions that have been drawn include:

- Reconciled research and viewpoints of complexity from both system-centric (cybernetics) and human-centric (human factors) fields of study.
- Enumerated several intermediary factors that affect the tradespace between human and system performance and complexity.
- Provided a model of *how* different types of complexity degrade each level of SA.
- Made progress towards a framework or method for consideration when designing human-machine interfaces for complex systems.

B. Limitations

A concept and notional model of effective variety have been presented, and several conclusions and hypotheses have been derived from it. However, it would be myopic to not acknowledge the different limitations associated with this initial effort.

The initial concept and model assumes a single user, single interface system. This simple human-system configuration is not always the case, and is growing increasingly less common still. The growing prevalence of Human-Agent Collectives (HACs), where humans and agents engage in more fluid relationships to achieve the goals of the collective [1] drives the need for a multi-human, multi-system model that is inclusive of shared mental models, shared SA, and team decision making dynamics [28].

The "Intermediary Factors" identified in Fig. 2 are treated as a "black box" in this notional model, rendering it grossly incomplete. There is a considerable corpus of literature on how different types and levels of automation affect SA and decision making [25], and how trust in automation [26, 27] drives complex human-machine interactions. Individual differences have also been acknowledged, but not explored to sufficient detail in this incipient effort. These intermediary factors need to be explored in depth before any substantial theoretical contribution can be put forward.

Finally, there is a considerable amount of brittleness in the concept since it is composed of multiple theories and findings, each which are largely context-dependent. When the component axioms from these theories are fused into a larger model, the model inherits the restrictions and contingencies of the subordinate theories [29]. This inherent brittleness makes this model of calibrated complexity somewhat of a "folk theory." Folk theories are still valuable topics of inquiry, as they bridge gaps between mental conceptions of phenomena and objectively-demonstrated principles of science [17]. Reference 6 has echoed this sentiment, showing that incomplete or notional theories have merit so long as they provide considerations and intuitions towards effective system design.

C. Future Work

This initial paper has described the concept of effective variety and presented a notional model of how complexity affects human-system performance in dynamic decision making tasks. Future work on this concept will involve performing more research on the different interactions within the notional model, refining the model, and testing the different hypotheses that were previously stated. Specific research goals include:

- Address how complexity affects system performance specifically in regarding interfaces.
- Address how complexity affects judgement and decision making in rational and naturalistic models (separate from SA).
- Model how intermediary factors such as automation, trust in automation, individual differences, and expertise mediate the relationship

between complexity and dynamic decision making.

- Develop numerical methods to measure, model, and simulate limits of human capacity for coping with complexity under time pressure.
- A diagnostic or checklist for system designers to assess the types and quantity of complexity present in a system interface design, and whether it will be calibrated appropriately based on the intended users and operational context.

Having achieved these near-term objectives, the ultimate goal will be to develop an integrated theory of complexity and dynamic decision making in human-system teams that has a formal mathematical description.

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