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Modelling Human Attributes in Autonomous Systems Operations

Jun Wang and Les Kosowski

Joint and Operations Analysis Division
Defence Science and Technology Group

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Joint and Operations Analysis Division
Defence Science and Technology Group

DST Headquarters,
Department of Defence F2-2-03
PO Box 7931
Canberra BC ACT 2610

www.dst.defence.gov.au
Telephone: 1300 333 362

EXECUTIVE SUMMARY

Unmanned Systems (UMS) have the potential to provide significant benefits when used in military operations that are dangerous, dirty, and/or dull; the principal benefit cited in a variety of literature is of reducing the risk of human casualties. Other claimed benefits of UMS suggest they can enhance situational awareness, reduce human workload, and improve mission performance at a reduced cost. These are worthwhile benefits; however, war is a particularly human endeavour in which current technology cannot replicate the understanding, intuition and decision making of human combatants. Human-UMS teaming is seen as a desirable state in which humans supervise, task and interact with robotic systems. This is the semi-autonomous mode of operation of UMS, also known as human supervisory controlled (HSC) autonomy; for example, the USAF fleet of long endurance Unmanned Aerial Vehicles (UAVs). In HSC UMS military employment, there is evidence from simulator-based experiments that the operators' attributes have an impact on the UMS performance. However, it is recognised that while the autonomous systems are modelled with high fidelity, the human element is poorly represented for the human-operated systems in extant closed-loop combat simulation models. Therefore these simulations, when applied to model HSC UMS employment, can lack proper characterisation of human attributes. In this report we review the literature to investigate examples where human-attributes have been modelled in other simulation paradigms, system dynamics (SD) and discrete event simulation (DES) in particular.

More specifically, based on our review, we have identified five human attributes (trust, impact of human interventions[1], cognitive workload, attention allocation and situation awareness, and human learning) that have shown to have an impact on UMS system performance. We discuss how each of the identified human attributes is implemented, and contributes to the modelling and measurement of system performance in the SD and DES models.

The differences of SD and DES approaches are compared and analysed. Lessons learnt from SD or DES models are described. These lessons could to inform combat simulation practitioners to enrich the existing high-fidelity combat simulation models.

[1] This is called 'human value-added through interventions' in the original literature and this is maintained in the main text.

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CONTENTS

GLOSSARY

CHAS	Collaborative Human-Automation Scheduling
CLD	Causal loop diagram
DARPA	Defense Advanced Research Projects Agency
DES	Discrete event simulation
DSS	Decision support system
EP	Expected performance
HPS	Human processes and states
HRI	Human robotic interaction
HSC	Human supervisory control
H-UMS	Human-UMS (team)
MBC	Management by consent
MBE	Management by exception
MME	Metrics of mission effectiveness
PAC	Perceived automation capability
PAL	Performance and Attention with Low-task-loading
PPG	Perceived performance gap
PPP	Perceived present performance
SA	Situation awareness
SFD	Stock and flow diagram
SD	System dynamics
SME	Subject matter expert
tPPP	Time to change PPP
UAV	Unmanned aerial vehicle
UGV	Unmanned ground vehicle
UCGV	Unmanned combat ground vehicle
UMS	Unmanned system
USARL	US Army Research Laboratory

1. INTRODUCTION

Unmanned systems[2] (UMS) [1] have been playing an increasing role in military operations as they provide benefits in reducing the risk of human casualties in 3D (Dangerous, Dirty and Dull) operational tasks [2]. It is claimed that 'Unmanned systems have proven they can enhance situational awareness (SA), reduce human workload, improve mission performance, and minimise overall risk to both civilian and military personnel, and all at a reduced cost' [2]. It is recognised, however, that while UMS have been doing some soldiers' jobs, 'war remains a human endeavour especially for Land Forces' and 'technology will not replicate human judgment, intuition, morality or understanding' for some years [3]. Consequently, Human-UMS teaming is a key challenge to develop 'the capacity for humans to supervise and task large robot teams and interact with robotic teammates' [4].

There are indications, from the case studies of the US Army Research Laboratory's (USARL) Human Robotic Interaction (HRI) Program, that human attributes have an important impact on UMS performance [5, 6]. For example, USARL HRI research has suggested that increased workload due to multitasking can lead to an increased risk for personnel (because of compromised soldier's SA), and degraded mission performance [5-7]. Moreover, the level of automation can have a negative impact on operator performance, such as increased mental workload, reduced situation awareness, over-trust and skill degradation, which can, in turn, negatively impact UMS performance [8, 9]. Therefore, before the acquisition and deployment of autonomous systems, military organisations should conduct analytical analysis in order to identify the limits and potential issues associated with operators' behaviours.

There are several analytical techniques that have been in use in military operation analysis to investigate human-UMS teaming. These include, but are not limited to, field trials, simulator-based experiments and simulation modelling techniques [10]. One of the frequently used simulation modelling techniques is closed loop (constructive) combat simulations where there is no modeller interaction with the simulation once it starts running [11]. However, it is recognised that, while the autonomous systems are modelled with high fidelity[3], the human element is poorly represented for the human-operated systems in extant combat simulation models [11, 12]. Blais and McGregor suggest that it is a challenge to characterise human attributes in combat simulation models to provide an analytical basis that can demonstrate

[2] Unmanned systems is a commonly understood term that has been defined in [1] and used in many of the documents referenced in this report. The authors are aware of alternative terms such as 'uninhabited' and 'un-crewed' but have chosen the 'unmanned' term for consistency throughout this report.

[3] In the authors' opinion, this fidelity is confined to the physical aspects of systems; e.g. mobility, lethality, survivability, sensing and targeting.

the benefits, limitations and challenges before introducing UMS into service [11, 12]. This report is a review of the human attributes which are important for combat simulation models.

2. HUMAN ATTRIBUTES

Huang has described four modes of operations of UMS [1]:

1. Remote control where the human operator controls a UMS on a continuous basis without the assistance of video or other sensory feedback.
2. Teleoperation where the human operator controls a UMS on a continuous basis with video or other sensory feedback.
3. Semi-autonomous where the human operator plans the mission for a UMS and intervenes whenever it is necessary.
4. Fully autonomous where there is no human intervention required for a UMS or a team of UMS to complete its assigned mission.

In terms of the human-machine command-and-control relationship [13], remote control and teleoperation modes are generally described as 'human in the loop', while the last two modes are described as 'human on the loop' and 'human out of the loop', respectively. This study is aimed at the 'human on the loop', or 'human-supervised autonomous' [13] since, as the US Department of Defence has stated, 'It should be made clear that all autonomous systems are supervised by human operators at some level, and autonomous systems' software embodies the designed limits on the actions and decisions delegated to the computer'[14].

A shift from remote control to semi-autonomous, leads to the soldiers' role in direct manual control of UMS being reduced, but more demanding in cognitive activities in terms of planning and decision making. This change in control 'from lower level skill-based behaviours to higher level knowledge-based behaviours is known as human supervisory control (HSC)' [15].

2.1. Human supervisory control

HSC is defined as a relationship between the human operators and the system in use to carry out a mission, which can be represented by Figure 1 ([16] cited in [15]).

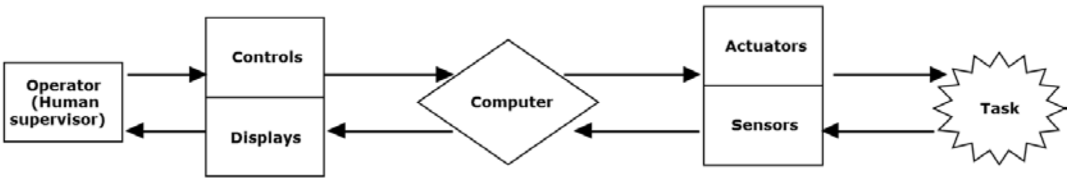

Figure 1. Human Supervisory Control (reproduced from [16]).

In HSC, in contrast to Manual and fully automatic controls [17], the operator intermittently issues instructions, through a computer with decision support systems (DSS or automation for simplicity), to actuate the system to complete tasks. Once tasks are completed, information relevant to the impact of the system actions is fedback via sensors to the computer and operators for monitoring and further instructions. The operators can intervene to alter the system behaviour when required. HSC can be simply described as the control structure where 'humans supervise computers and computers perform the direct control [18]'. Humans can then focus on high-level activities such as [16]:

- *planning* what task to do and how to do it
- *teaching* (or programming) the UMS what was planned
- *monitoring* the UMS action
- *intervening*, or taking over the control from the automation
- *learning* from experience.

The systems in HSC are assisted by embedded intelligent software (DSS) in scheduling (such as task allocation), terrain reasoning, pathfinding and obstacle avoidance under the operators' guidance [19].

Depending on the level of automation, UMS can be supervised using different approaches of 'management-by-consent' (MBC) or 'management-by-exception' (MBE) [15]. MBC approach requires operators to approve the decisions prior to UMS execution, while the MBE approach requires the operators to monitor UMS actions to reject the UMS' decisions, if necessary, within a limited period of time [15]. A key concern with MBC is that operator workload can be saturated if the number of approvals is high [15]. In MBE, automation bias (a decision bias when operators do not check the UMS' decisions) could occur due to operator over-trust of UMS [15]. Therefore, the implementation of either approach needs to consider the impact of the human attributes on system performance [15].

A key parameter for Human-UMS performance is the operator-to-system ratio. While the current development is aimed at, for unmanned ground vehicle (UGV) in particular, one operator controls one UGV such as Russia's Uran-9 unmanned combat ground vehicles (UCGV) [20] or BAE's Armed Robotic Combat Wingman Vehicle (previously known as the Black Knight) [21]. There is a demand, however, for the development of system architecture to allow a single operator to control multiple UMS [22]. The US DARPA's[4] CODE[5] program plans to develop a system to allow one pilot to control a team of unmanned aerial vehicles

[4] Defense Advanced Research Projects Agency
[5] Collaborative Operations in Denied Environment

(UAVs) [23]. In simulated environments, simulator-based trials have tested the cases for one operator to control multiple (up to eight) UGVs [24], teams of heterogeneous UMS (one unmanned surface vehicle plus three UAVs [25], or one UGV, one UAV and a manned ground vehicle [26]). As the number of supervised UMS increase, adverse impacts on UMS performance from human attributes, such as cognitive workload and SA are expected to increase as well, which further enhances the necessity of including human attributes in simulation models [27].

The 'system performance' (or simply performance) in this report means the UMS performance measured by the metrics of mission effectiveness, for example UMS search speed in a military search mission [28]. Since UMS in this study are subject to supervisory control by an operator; the references to operator performance will always impact system performance, directly and/or indirectly.

2.2. Human attributes identified as important in HSC

To investigate the human-factor effects on the system performance, the following attributes have been identified as important [28]:

- trust
- human value-added to performance through interventions
- cognitive workload
- attention allocation and situation awareness
- human learning.

Based on the evidence from simulator-based experiments, these attributes collectively characterise the major human effects on HSC-UMS performance (see [28] and references therein). The definitions and their impacts on performance are discussed further in each subsection.

2.2.1. Trust

There are several definitions of human trust of UMS; a highly cited definition is "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" [28]. This definition of trust has been used in studies of military Human-UMS in HSC settings [26, 29].

Over-trust can result in automation-bias, where operators are over-reliant on the automation and do not check to ensure automated decisions are correct [15]. In situations of under-trust, operators may override most of, if not all, the decisions from the decision support systems [26]. Over and under trust can lead to misuse and disuse of the UMS, which can negatively impact the system performance [26].

2.2.2. Human value-added to performance through intervention

This attribute describes the level of motivation of an operator in providing guidance to the UMS through interventions (i.e., changing the UMS recommended plan of action). Simulator-based trials have demonstrated that motivated human operator intervention did improve system performance, especially when the system experienced 'brittleness' [28]. 'Brittleness' occurs when the UMS is incapable of responding properly to unexpected (un-programmed) changes in the environment such as platform failures, new missions, and weather changes [28].

2.2.3. Cognitive workload

Cognitive workload is defined as the mental resource demand (generated by the task load) on the operator, which is a restraining factor on operator performance [26].

One metric proposed in measuring operator workload is utilisation[6] which is defined as the percentage of operator busy time during a mission period [11, 27]. In the simulator-based experiments, operators were considered as busy when they were engaged in decision-making tasks, such as intervening to replan the path of a UMS or approving weapon engagement [11, 27]. Operator workload does not include system monitoring tasks [27].

Researchers have shown that cognitive workload has an important impact on operator performance (see [27] and references therein). The operator performance as a function of workload can be represented by an inverted-U curve, which was inspired by Yerkes-Dodson Law [30]; a bell-shaped curve which shows that operator performance peaks when workload is moderate [26]. While high workload (cognitive overload) can be detrimental on operator performance, low workload can lead to a lack of sustained attention, resulting in boredom and degraded operator performance as well [11].

2.2.4. Attention allocation and situation awareness

Operators in HSC, for the context of controlling multiple-UMS in particular, are required to allocate their attention among a set of dynamic tasks. This set of tasks can include monitoring and intervening behaviours of each UMS in the team, or different mission aspects for one UMS [24, 27].

Metrics for measuring attention allocation have been proposed, which include time [27], frequency [28] and system performance cost [29] of task switching. The impacts of attention allocation on system performance have been studied by simulator-based trials [27-29].

[6] There are other subjective metrics used in measuring workload; e.g. NASA task load index (see [29] and references therein).

Inefficient attention allocation and information processing can lead to decreased situation awareness (SA).

SA is defined as “the *perception* of the elements in the environment within a volume of time and space, the *comprehension* of their meaning, and the *projection* of their status in the near future” [8]. Decrease in SA negatively impacts on operator decision-making [26].

2.2.5. Human learning

This attribute refers to the knowledge gain by operators during supervision of UMS throughout a mission. The learning is classified in two forms: long-term and short-term [26]. The long-term learning refers to the change of the operator’s expectations of system performance [26]. Short-term learning refers to the learning curve of the operator in using the user interface in controlling the UMS and the efficiency in reading, interpreting and analysing the feedback information from UMS [26].

3. MODELLING HUMANS IN SYSTEM DYNAMICS SIMULATIONS

System Dynamics (SD), initially named 'Industrial Dynamics' [31], originated from the theory of non-linear dynamics and feedback control developed in mathematics, physics and engineering [32]. SD investigates systems behaviour over time by analysing structures and interactions of feedback loops [7], time delays between actions and effects [32]. SD focuses on the structure of processes and information flow, which is collectively referred to as the structure of information feedback loops in management systems [34]. 'Intuitively, a feedback loop exists when information resulting from some action travels through a system and eventually returns in some form to its point of origin, potentially influencing future action' [35]. Mathematically, feedback is the phenomenon where changes in the values of a variable indirectly influence future values of the same variable [33]. SD can be viewed as a theory of structure of feedback loops [36].

In Human-UMS systems, especially in HSC, the operator controls the autonomous systems via feedback. Therefore, given SD's focus on feedback, SD is well placed to analyse Human-UMS teaming.

SD uses causal loop diagrams (CLDs) to qualitatively capture the structures and interactions of feedback loops. A causal-loop diagram consists of cause and effects variables (letters) and causal links (arrows). A causal link connects a cause variable near the tail of the arrow to an effect variable near the head of the arrow. Each causal link is assigned a sign either positive (+) or negative (-), called link polarity. A positive link from one variable X to another variable Y means that either X adds to Y, or a change in X results in a change in Y in the same direction [32]. Similarly, a negative link from X to Y means that either X subtracts from Y or a change in X results in change in Y in the opposite direction [32]. The notation '+/-' on a link indicates that the action will depend on the particular circumstance. Moreover, a feedback loop also has a sign assigned. The sign of a loop is determined by the signs of all links that make up the loop. More specifically, a loop is called positive (or R for reinforcing) if it contains an even number of negative causal links; a loop is called negative (or B for balancing) if it contains an odd number of negative causal links [32]. While a reinforcing loop tends to create change that drives the system away from its original condition, a balancing loop tends to create change that drives the system toward its original condition or toward a goal.

[7] A feedback loop is a closed sequence of causes and effects[33].

SD simulation models are represented by stock and flow diagrams (SFDs) with two fundamental ingredients called stock and flow variables, respectively [32]. Stock variables (also called state variables or levels) describe the states of the system, while flow variables (also called rate variables) depict the rates of change of stocks. Stocks are accumulations of their flows, which are defined mathematically as the integration of net flows, i.e.

$$Stock(t) = \int_{t_0}^{t} [Inflow(s) - Outflow(s)]ds + Stock(t_0),$$

where $Stock(t_0)$ is the initial stock value. $Inflow(s)$ and $Outflow(s)$denote the values of the inflow and outflow to $Stock(t)$ with $s \in (t_0, t)$ being the integration variable [32]. Conversely, the net flow determines the rate of change of any stock, i.e., its time derivative, by the differential equation below [32],

$$\frac{d(Stock)}{dt} = Inflow(t) - Outflow(t).$$

SD modelling of human attributes, in the context of military employment of UMS, (Clare [28] and Gao [37]) is reviewed in the next section. Clare's CHAS (Collaborative Human-Automation Scheduling) model [28] was built to simulate one operator in supervising three UMS in a mission of searching an area of interest. Gao's PAL (Performance and Attention with Low-task-loading) model [37] examined the scenarios of human-automation interaction of long duration and low workload. As part of this review, we have fully replicated both the CHAS and PAL SD models and obtained similar outputs when the inputs provided in the references [28, 37] are employed.

3.1. SD modelling of trust

Trust, defined as the operator's attitude towards the automation capability, is modelled as a dimensionless percentage (0-100%) stock variable. The change of the operator's trust in automation is caused by an inflow 'Change in Trust', which is defined as:

Change in trust = (Perceived automation capability-Trust)/(Trust change time)

which states that the trust in automation is adjusted according to the difference between the perceived (observed) automation capability and the operator's expectation towards the automation capability (trust). The trust will increase when the observed is higher than the expected and decrease otherwise.

There are two input constant parameters in modelling trust: 'Trust change time' and 'Initial trust'. The denominator of 'Change in trust' is 'Trust change time', which states that the trust adjustment is not instantaneous (representing the inertia of Trust changes originated from the information accumulation process [35]). 'Initial Trust' depends on the operator's prior experience and knowledge about the automation under supervisory control (see [28] and references therein). Both the 'Trust change time' and 'Initial trust' can be estimated by model fitting to simulator-based trials [28].

'Perceived automation capability' (PAC) is modelled as a nonlinear function of 'Perceived performance gap' (PPG), a variable describing how far the automation performance differs from the operator's expectation. An inverse logistic function was used to model PAC in [28], while a scaled linear function was used in [38], so that PAC ∈ (0,1).

The attribute 'Trust' impacts on system performance via the number of operator interventions. Higher trust usually results in an operator accepting the automations' decisions, while lower trust generally leads to more interventions where the operator takes more control by overriding the automation generated decisions. The number of interventions influences system performance through the 'human value-added through intervention'. A CLD summarising the causal relations of Trust modelling is displayed in Figure 2.

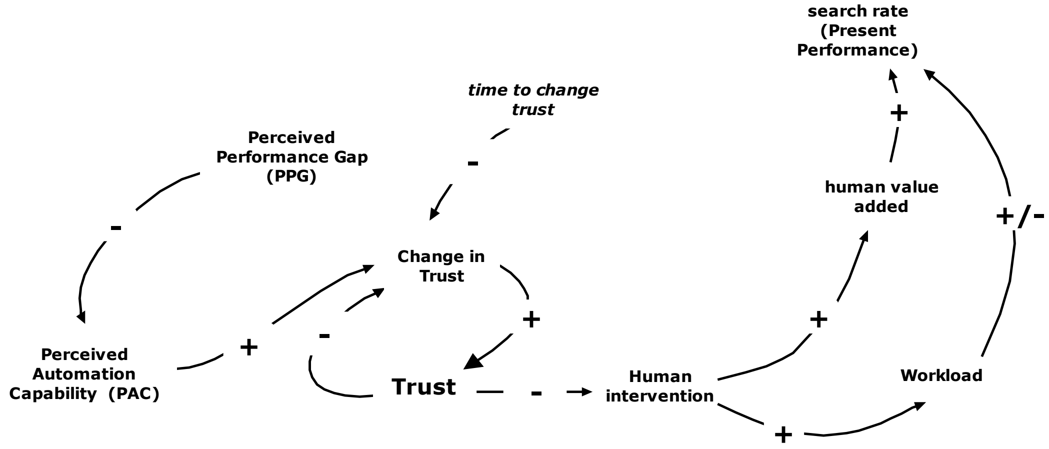

Figure 2. A CLD description of Trust modelling.

3.2. SD modelling of human value-added through interventions

Based on two simulator-based trials of military search missions [28, 37], increase in intervention positively impacts on system performance. The relationship between the system performance (measured by the speed of search) and the 'human value-added through intervention' was modelled by a logistic function in [28] , and a linear function in [37]. Both the expressions (nonlinear [28] and linear [37]) are based on the assumption that the operator's intervention improves system performance. On the other hand, the increase in interventions increases the operator's workload which may negatively impact on system performance. The impact of human intervention on system performance is shown by two causal pathways on the right side of Figure 2.

3.3. SD Modelling of cognitive workload

Inspired by the Yerkes-Dodson Law [28, 37, 39], the impact of workload on operator performance (measured by task processing rate) is implemented by an inverted U-shaped curve, which is depicted by a notional diagram [28] shown in Figure 3.

The curve shows that either low or high workload will degrade operator performance. On the left of maximum operator performance, an increase in workload from 'low' to 'moderate' will have a positive effect in improving operator performance. Once the workload is beyond the point corresponding to the performance peak, operator performance will suffer. In SD models, this inverted U-shaped relationship is modelled by two feedback loops representing two causal pathways which can be described by the simplified CLD shown in Figure 4 [28, 37, 39].

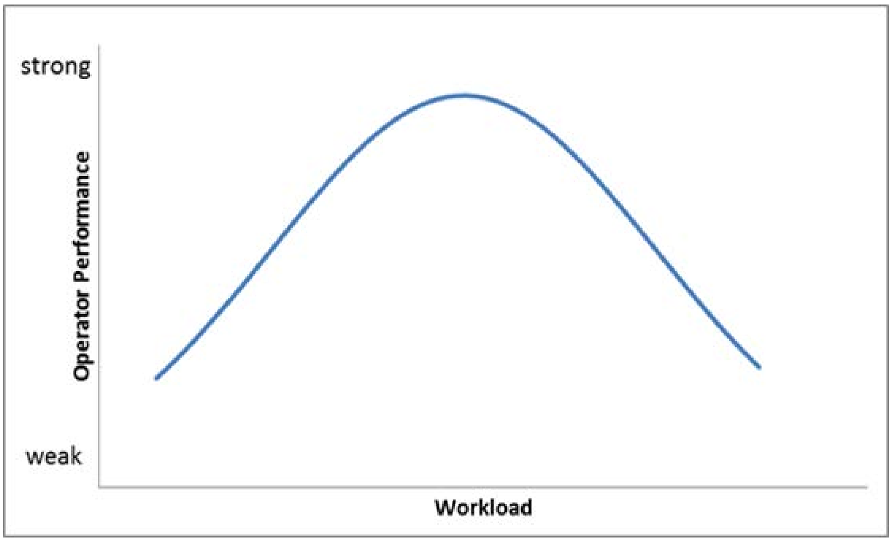

Figure 3. An indicative operator performance vs. workload curve.

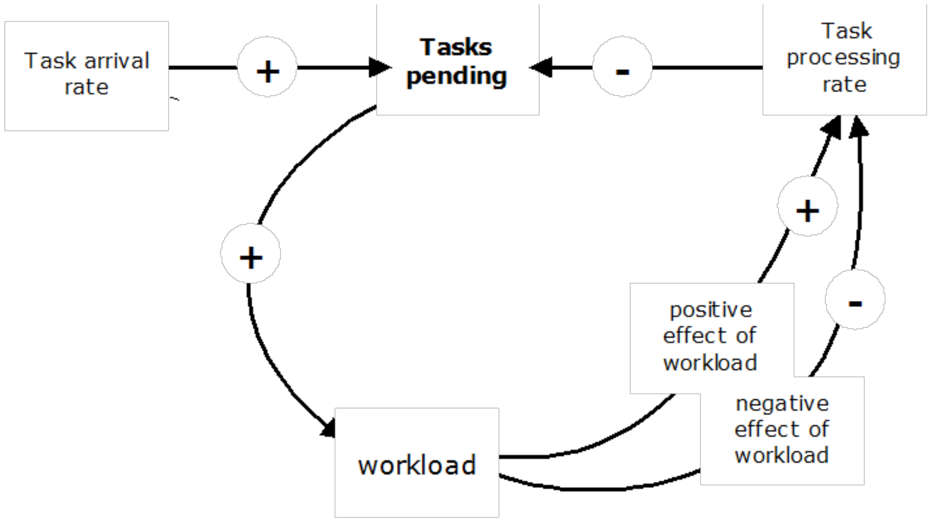

Figure 4. CLD description of modelling workload impact on task processing rate (the measure of operator performance).

As can be seen in Figure 4, an increase in 'Tasks pending' leads to an increase in workload. If the increased workload falls in the upward-sloping side of the curve in Figure 3, it leads to an increase in 'Task processing rate', which ultimately reduces 'Tasks pending'. This loop is balancing (B-loop) to offset the increased 'Task pending'. However, if the increased workload falls in the downward-sloping side of the curve in Figure 3, it leads to a decrease in 'Task processing rate', which leads to an increased accumulation of 'Tasks pending'. This loop is reinforcing (R-loop) to amplify the increased 'Tasks pending' further.

The 'positive effect of workload' and 'negative effect of workload' were implemented by logistic[8] mathematical functions [37], or empirical numerical table functions [28, 39].

3.4. SD modelling of attention allocation and situation awareness

Attention allocation can be modelled simply as an input parameter, tPPP, representing the time for the operator to detect changes in the perceived system performance [28]. A lower tPPP indicates higher attention allocation efficiency of the operators who are required to concentrate on the primary task of monitoring the UMS performance and their alerts [28]. tPPP affects the 'Perceived performance gap' (PPG), which affects Trust through 'Perceived automation capability' (PAC) (see 2.2.1).

There are three levels of SA [8]:

[8] A variety of sigmoid shaped functions, for example see http://xaktly.com/LogisticFunctions.html (downloaded on 6 November 2019).

- *perception* of the elements in the environment within a volume of time and space
- *comprehension* of their meaning
- *projection* of their status in the near future.

In SD CHAS model [28], three levels of SA were modelled by the operator's Perceived Present Performance (PPP) of the UMS, the operator's understanding of Perceived Performance Gap (PPG), and the operator's projection of the UMS Expected Performance (EP) [28]. The mapping of the three levels of SA [8] to model variables [28] is summarised in Table 1 below. The simplified CLD in Figure 5 depicts the relationship between attention allocation and SA [28].

Table 1. Mapping of SA elements to SD model variables

Three elements of SA	**Model Variables**
Perception	PPP (The operator's Perceived Present Performance)
Comprehension	PPG (The operator's understanding of the UMS performance gap between the expected and actual)
Projection	EP (The operator's projection of future UMS performance)

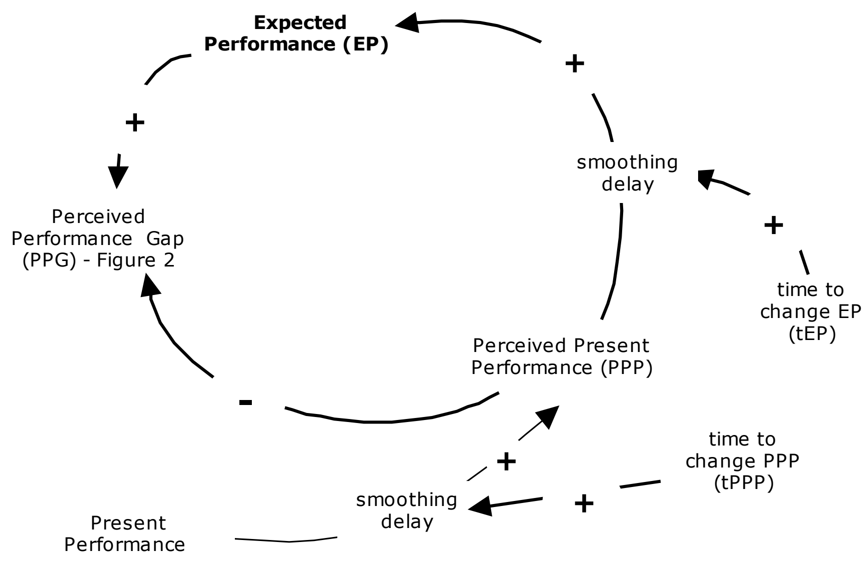

Figure 5. CLD description of impact on performance due to attention allocation and situation awareness.

3.5. SD modelling of human learning

The ‘long-term learning’ defined in section 2.2.5 is modelled as time-delayed adjustments in operator’s perceived performance, expected performance, and trust level (see the CLD in Figure 2 or the CLD of Clare’s CHAS model [28] in A).

The ‘short-term’ learning attribute represents the learning effects as operators become more proficient in supervising the UMS, which can be estimated by ‘Time to replan’; i.e. the length of time the operator is required to modify the DSS generated plan of action [28]. For Clare’s CHAS model, the effect of ‘short-term’ learning is negligible; hence it was removed from the final version of the model.

4. MODELLING HUMANS USING DISCRETE EVENT SIMULATIONS

Discrete event simulation (DES) is a technique to model queuing-based systems. The fundamental building elements of a DES model include events, arrival processes, service processes, and queuing policies ([40] cited in [25]). For a DES model of HSC of UMS, the human operator is modelled as a task-processing server [25]. The required inputs for a DES model are mainly the distributions of the task-arrival rates and the distributions of task-processing times. These distributions can be estimated or drawn from previous experimental data [25]. 'DES models are by definition stochastic in nature and deal with distinct entities, scheduled activities, queues and decision rules'[41].

DES modelling of HSC of single operator multi-UMS teams is based on four fundamental building blocks [42], namely:

- Events, which represent tasks to be processed by the operators. There are three types of events that can occur:
    1. UMS generated events requiring operator judgment and decision making (e.g. a detected object requires operator identification)
    2. operator-generated events (e.g. the operator's intervention to alter UMS existing plan)
    3. environmental events (e.g. weather changes requiring operator interaction).
- Arrival processes, which describe the processes by which events come to an operator's attention. There are two types of event-arrival processes: dependent and independent. For a dependent-arrival event, the generation depends on the processing status of events created previously. For an independent-arrival event, the generation is determined by a probability distribution, irrespective of the servicing-status of the previously-created events (e.g. an emergent target). The arrival processes of UMS-generated (e.g. for the situation where a UMS-captured image requires the operator to analyse, and the generation of a second image from the same UMS depending on the completion of the previous analysis) and operator-generated events (e.g. event of goal-reassignment of UMS depending on the completion of some previous events like target acquisition) are dependent-arrival [42].
- Service processes, which describe the delay before events receive operator attention, and how fast the events can be processed by operators.

- Queuing policies, which determine the queue-ranking rules used to prioritise the events in the queue to be processed.

In the HSC context of military employment of UMS, DES has been applied to model the surveillance tasks in urban coastal and inland terrains. Simulator-based experiments were conducted for a single operator controlling a team of simulated UMS [30, 42-46] or a team of operators supervising a team of simulated UMS [47].

4.1. DES modelling of Trust

It appears that DES modelling of HSC within military UMS employment [30, 42-47], that trust is not modelled explicitly; this compares with SD simulation models (see 3.1) where it has been. Operator trust is implicitly reflected through ‘management strategy’ [30, 42-46] which determines how frequently an operator wants to intervene the UMS plan. The operator intervention is modelled through a probability distribution of operator-generated events.

4.2. DES modelling of human-value added through intervention

In DES models [30, 42-46], operator intervention manifests itself through operator-induced events; for example, in re-planning DSS-generated sub-optimal routes. These interventions improve the system performance in terms of the number of tasks completed [42]. On the other hand, the interventions will add to operator workload, which will negatively impact on operator performance.

4.3. DES Modelling of cognitive workload

In DES modelling of workload, operator utilisation is used as a proxy measurement [30, 42-47]. Utilisation is defined by the percentage of busy time for an operator in task-processing during a mission period (see 2.2.3). The impact of workload on operator performance is implemented through a penalty function which represents degradation of SA due to over- or under-utilisation [42, 45, 46]. The penalty function χ , as a function of workload, is modelled by a concave upwards parabolic function (see Figure 6). The effect of this penalty is to create additional platform waiting times before the operator notices the needs of the system [42, 45, 46].

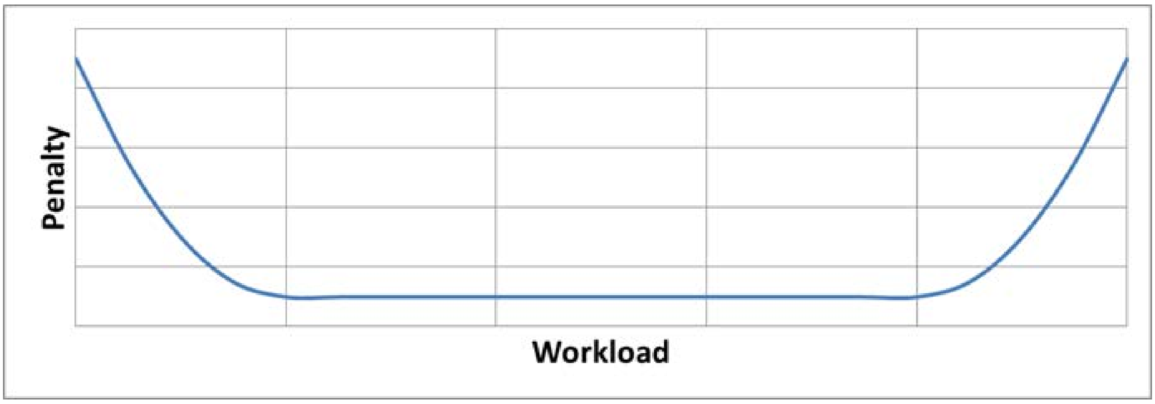

Figure 6. Penalty as a function of workload (the horizontal part of the curve is zero penalty)

4.4. DES modelling of attention allocation and situation awareness

For multi-UMS under HSC, the way by which the operator will supervise the different platforms is based on operator attention allocation. Two attention allocation strategies have been implemented, 'switching strategy' and 'management strategy', respectively [42, 45, 46].

The switching strategy determines the order of preference to address the different tasks from different UMS, which can be implemented through queuing policies (e.g. First In First Out or Priority based) [45]. The management strategy is mirrored in the amount of operator-induced events, which is described by a probability distribution [45]. The management strategy reflects the operator trust implicitly.

Operator situation awareness is modelled as function of workload which impacts on task waiting time.

4.5. DES modelling of human learning

Human learning is not represented in DES models.

4.6. DES modelling of 'backup'

SD and DES models reviewed up to this point represent a single operator controlling multiple UMS. A DES model of the teamwork (a team of two operators) in HSC of multiple UMS was reported in 2014 [47]. The model simulated team 'backup' behaviour, which is defined as 'the extent to which team members help each other performing their roles' ([48] cited in [47]).

In the DES model [47], team work was characterised by the following features:

- Queue-sharing, where the operators shared control of multiple UMS in processing the events in the same queue.
- Team communication, which manifests itself in the extended service time. The positive impact of team communication is mutual operator-performance monitoring (modelled as a higher probability of error correcting). The negative impact is the reduced number of processed tasks in a certain time period.

The DES model with 'backup' was able to replicate the outputs of a simulator-based experimental study on operator team performance measures [47]. The conclusion from this study was that the 'backup' behaviour was beneficial when the task load is unevenly distributed, but 'backup' behaviour was unnecessary if task load is evenly distributed with low uncertainty [47].

5. DISCUSSION

Simulation models have been used extensively in Defence to support system acquisitions by consolidating known factors into a computer program and then using it as a surrogate for the actual system. The models assess the system performance by calculating the metrics of mission effectiveness (MME) in a representation of the expected operation environments. For this assessment to be valid, all the attributes (or variables) that make a significant real world contribution to MME should be included in the models. In the HSC context of military UMS deployment, the existing combat simulation models could improve evaluation of system performance through better inclusion of human attributes as they have been shown to have significant impact on mission performance in many operational contexts [5, 6, 11]. This literature review has surveyed published literature on human attributes modelling in SD and DES, which could inform combat simulation communities to improve their models.

It seems counterintuitive to state that the human attributes are important in Human-UMS modelling, since the introduction of automation, after all, does reduce or replace soldiers' roles in some tasks during an operation. This 'paradox' may be clarified by the characteristics of decision-making in HSC, where UMS make decisions which are not 100% trusted. In the situation of manual control, systems that are not part of the decision process, act by completely following the soldiers' intention (except in systems failure). Therefore, when 'machines' become part of decision processes, the factors influencing the operator's decision-making (as a controller of systems with intelligence) cannot be overlooked in the assessment of Human-UMS teaming.

There are several research publications on assessment frameworks of Human-UMS teaming [49-52]. One of these frameworks states (see [49] and references therein) that the two key outcomes (performance and safety) of Human-UMS are produced by 'Human processes and states' (HPS). This HPS takes the inputs (from UMS, operator, and environment) to generate the mission outcomes. Therefore it is necessary to include these key variables in describing the HPS in order to reduce potential biases in model assessment of performance, which is the product of HPS. There are three types of variables used in characterising HPS, which are identified as key attributes influencing Human-UMS performance [49]:

- Attitudes, representing what the operator feels, with 'Trust' as a primary attitude.
- Behaviours, representing what the operator does, with 'Reliance, Monitoring, and interaction with automation' as the main features.
- Cognitions, representing what the operator thinks, with SA and cognitive workload as important cognitive indicators.

Therefore, the human attributes that we have captured fit well with the framework proposed by experts in the field of human-machine interaction research [49]. The identified attributes are expected to be relevant to the modelling of any Human-UMS under human supervisory control performing a variety of military tasks. The table below summarises these attributes and their implementations in SD and DES models.

Table 2. The contribution of each of the human attributes to the measurement of performance in SD and DES models.

Human attribute	SD [28, 37]	DES [42, 44, 47]
Trust	Modelled explicitly as a percentage stock variable (changing with time). Impacted by perceived and observed system performance. Impacts on the frequency of human intervention.	Not modelled explicitly. Implicitly through 'management strategy', trust manifested itself through the operator intervention.
Human value-added through interventions	Impacted by the level of trust. It is assumed that intervention will improve system performance but increase workload.	Intervention manifests itself through the probability distribution of the number of operator-generated events. It is assumed that intervention will improve system performance but increase workload.
Cognitive workload	Defined by operator utilisation, a proxy for workload. Impacts on operator performance through task processing rate, either negatively or positively	Defined by operator utilisation, a proxy for workload. Impacts on operator performance through a penalty function to add extra task waiting time.
Attention allocation and situation awareness	Attention allocation can be modelled as a parameter tPPP (time to change PPP) describing the time required for the operator to change his/her PPP (Perception about the system Present Performance). SA is modelled by three variables: Perceived Present Performance (PPP), Perceived Performance Gap (PPG), and Expected Performance (EP), corresponding to three levels of SA (Perception, Understanding and Projection). PPG impacts on operator trust.	Attention allocation can be modelled by: • the switching strategy implemented through queueing policy • the management strategy implemented through the number of operator-induced events SA is modelled as a function of workload which impacts on task waiting time.
Human learning	Represented by dynamic adjustments of expected UMS performance (EP in Figure 5) and trust (in Figure 2) as the operator monitors the system performance.	Not modelled
Back up	Not modelled	Modelled by queue-sharing and team-communication for two operators' in controlling multiple UMS.

SD and DES are two simulation paradigms captured in this work in modelling humans in HSC military employment of UMS, with two CLDs presented in Appendices A and B, respectively, showing the causal relationships between human attributes listed Table 2. Moreover, the Stock and Flow diagram of CHAS simulation model [28] is displayed in Appendix C to illustrate the implementation of the CLD in Appendix A.

There are several publications that have analysed and compared the characteristics of these two simulation methods [41, 53-55], which are summarised below.

There are three fundamental components in building an SD model: stock (level), flow (rate), and auxiliary variables [32]. The status of the system being modelled is described by the stock variables while the dynamics is driven by flow variables. Mathematically, an SD model is a set of differential equations (or difference equations in simulation practice). SD is typically a deterministic method, and has advantages in dealing with problems where the main quantities of interest are continuously changing (e.g. trust). However, with extra effort, an SD model can include discreteness and uncertainty [56]. The "time slicing" technique is used to move simulation forward at equal time intervals [57].

The fundamental components in a DES model are: Events (generated by entities), Arrival Process, Resources, and Event handling, which collectively model queuing systems as they move forward through time [41, 58]. The status of the system being modelled is displayed as the number of events in waiting, being worked on, and whether the resources are busy, idle or in other states [41, 58]. Dynamics are driven by randomly arriving events which require processing by the system resources. Mathematically, a DES model consists of a set of probability distributions that determine the time points of event arrival, starting in a queue, beginning and then completion of processing. DES models are stochastic by nature and treat entities discretely instead of at an aggregated level of entity population. DES simulation progresses at a random time increment, which means that the states of the system are updated randomly when something (events) occurs (time handling being done by a calendar, a software created list of events that are scheduled to occur in the future) [59].

In practice, the data requirement of an SD model is much less than that of DES which requires and generates a large amount of data [41]. Moreover, like SD models, the "time slicing" [57] is a technique used in many of combat simulation models (e.g. CAEn, JANUS, CastForem, CombatXXI, SWORD). Therefore, the lessons learnt from SD modelling of human attributes can readily be transferred into combat simulations.

6. CONCLUSIONS

Based on the literature reviewed, this report summarises five human attributes which have been implemented in SD and DES models where UMS under HSC were employed in military missions. While modelling human attributes in closed-loop simulations may be at its early stage, considering that the captured publications are essentially from the same MIT (Massachusetts Institute of Technology) group [25], the impacts of operator attributes on UMS performance are well supported by the research outcomes of the USARL HRI program [5-7]. From a simulation modelling perspective, including human attributes, e.g. workload in DES model, did improve the model's predictions by rectifying over-predicted performance from a model without workload-attribute included [30]. We provide the following recommendations, as a starting point, for the combat-simulation community to consider:

- Inclusion of the workload-performance curve (Figure 3–like) to examine its effect on model outcomes. Models that include workload can provide guidance on UMS design, including automation levels, to inform optimal load to maximise performance [28].
- Inclusion of Trust (SD instantiation of trust in 3.1), a factor contributing to workload, to evaluate its impact on system performance. Models with trust can assist UMS design through decision capability in different operational contexts [38].
- Mathematical function forms of workload and trust in SD models [28, 37] can be used as the starting references, with the note however, the function parameter in [28, 37] were case-specific, which were obtained by fitting to the results of simulator-based trials.
- Where randomness is required to be modelled, as in DES modelling paradigm, the probability distribution used was the lognormal to model events arrival and service time, which provided the best-fit (to simulator-based experiments) in most cases [42]. Where there is no trial-data available, advice from subject matter experts (SMEs) should be sought; a uniform distribution will be starting selection for a two-points estimate (minimum and maximum) from SMEs, while a triangular distribution will be a candidate for a three-point estimate (minimum, maximum and the most likely).

Depending on the availability of quantitative metrics, model variables can be classified as 'soft' and 'hard' (p853 [32]). For 'hard' variables, quantitative metrics and data are available [32]. 'Soft' variables are those for which quantitative metrics and data are absent [32]. Therefore a proxy needs to be constructed for the 'soft'. Most of the variables depicting human attributes in this report are 'soft', which include goals, perceptions and expectations

[32]. Models containing 'soft' variables may be perceived as less accurate (or harder to model) than those with 'hard' variables only. However, to omit 'soft' variables in models "is equivalent to saying they have zero effect-probably the only value that is known to be wrong!" [31]. As such there is significant benefit for combat simulation communities to consider modelling humans in HSC UMS military employments.

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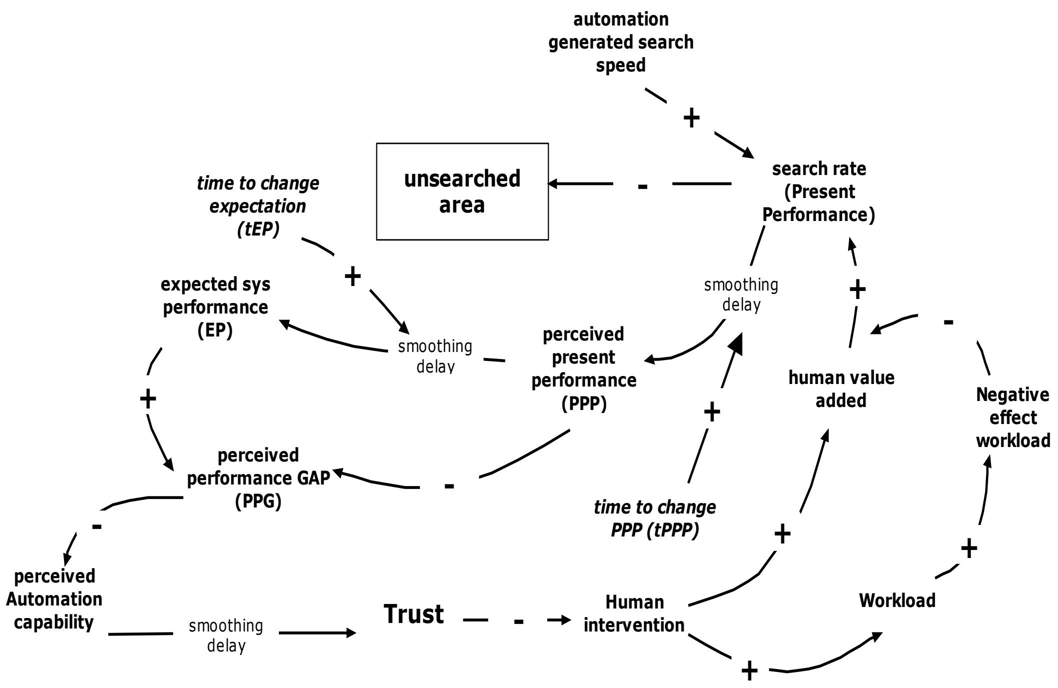
A. A CLD DESCRIPTION OF CLARE'S CHAS SD MODEL



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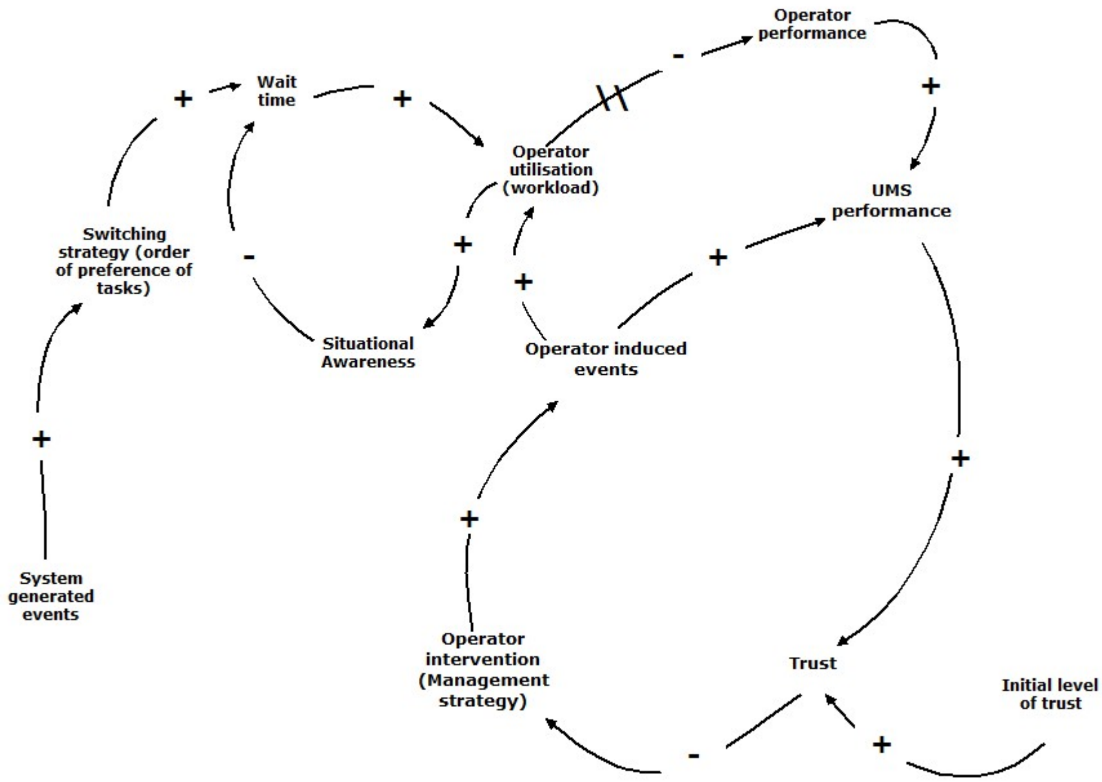
B. A CLD OF THE DES MODEL OF HUMAN ATTRIBUTES AND THEIR CONTRIBUTION TO PERFORMANCE



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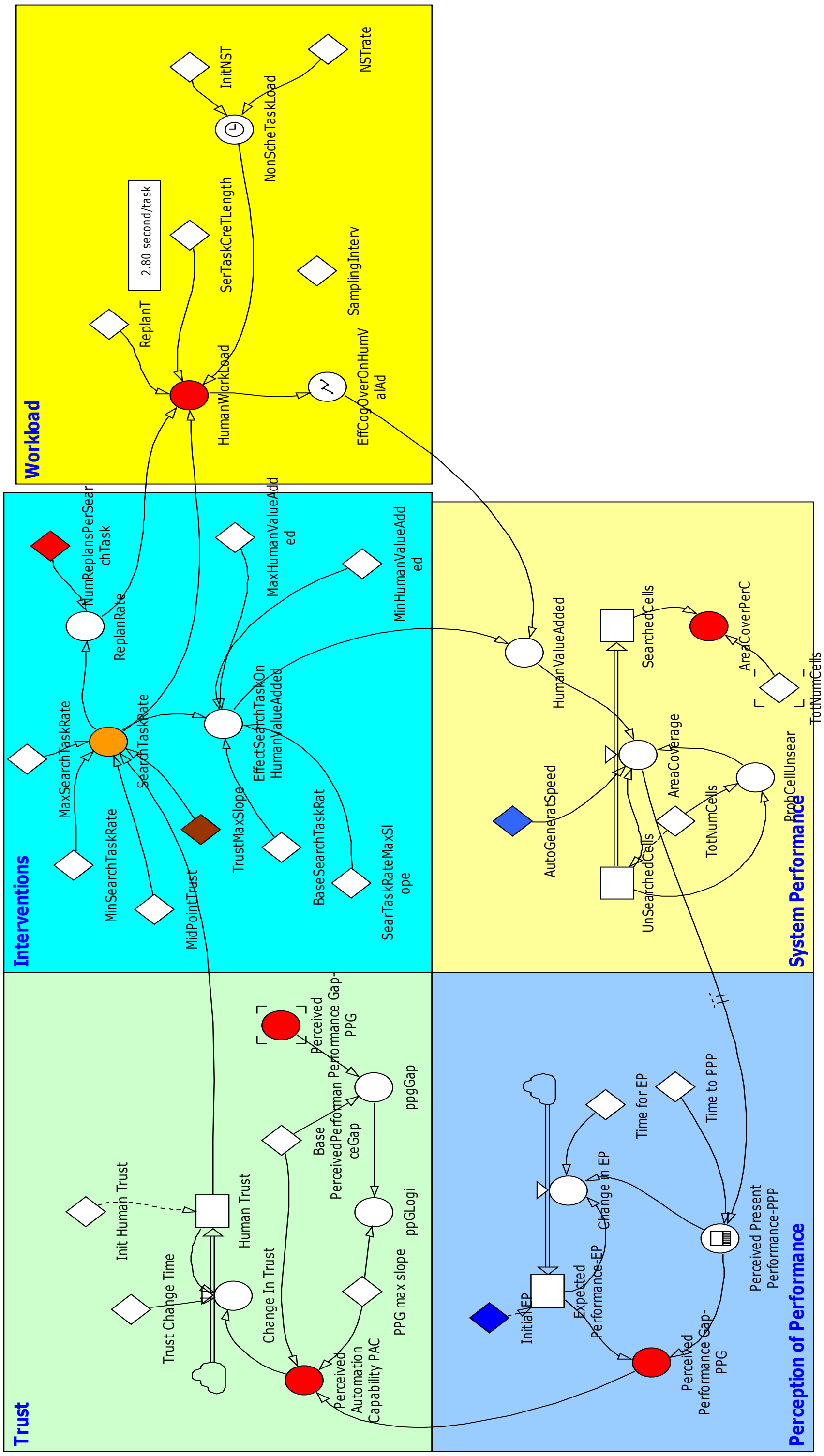
C. THE STOCK AND FLOW DIAGRAM OF CHAS SIMULATION MODEL (LOCALLY REPLICATED)



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