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Predicting Human-Robot Team Performance Based on Cognitive Fatigue

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***Abstract*—Human-robot systems are increasingly employed across various industries, such as transportation, military, emergency response, and manufacturing. During human-robot collaboration, cognitive fatigue accumulation significantly impacts the human operator's performance, particularly in teleoperation and shared autonomy. This fatigue accumulation can be dangerous and may lead to incidents in robot operations. Consequently, modelling human performance is crucial for understanding and evaluating human-robot systems for risk mitigation and efficiency enhancement. In this work, we propose a prediction model for human-robot teams based on Fitts' Law and the SAFTE model. The model takes into account the operator's cognitive fatigue level and mission requirements to predict whether the operator is suitable for executing the mission and the time required for the human-robot team to complete it. Furthermore, we present a case study on a hypothetical scenario, drawing upon human study data, to assess the model's applicability.**

***Index Terms*—human-robot collaboration, cognitive fatigue, performance prediction, robot safety**

I. Introduction

Predicting the performance of a robot for a specific task with given parameters is often straightforward. However, in the context of human-robot teaming, accurately predicting performance becomes a highly non-intuitive task due to the influence of human factors, particularly cognitive fatigue. Modelling human-robot team performance while accounting for cognitive fatigue presents significant challenges due to the inherent uncertainty in human behaviour, but doing so could yield valuable insights for a wide range of applications.

Fatigue is a well-known risk factor in the operation of machinery, including vehicles and robots. The Federal Aviation Administration (FAA) reports that 21% of the Aviation Safety Reporting System (ASRS) reports mention pilot or crew fatigue, with 3.8% of these cases directly attributing incidents to fatigue [1]. Similarly, the U.S. National Highway Traffic Safety Administration (NHTSA) estimates that driving under fatigue has caused $100,000$ crashes, leading to over $1,500$ fatalities and $71,000$ personal injuries [1]. While research on operator fatigue in the transportation industry is extensive, similar studies in robotics are limited. Nonetheless, available evidence highlights the dangers of fatigue accumulation in robotic operations. For example, a study analysing 237 robotics incidents found that 63.27% of these cases were directly caused by excessive action stemming from a lack of workforce, night shifts, insufficient relaxation, or fatigue [2]. Furthermore, 31.39% of the root causes for unsafe behaviour in robot operation cases were attributable to night shifts or fatigue accumulation.

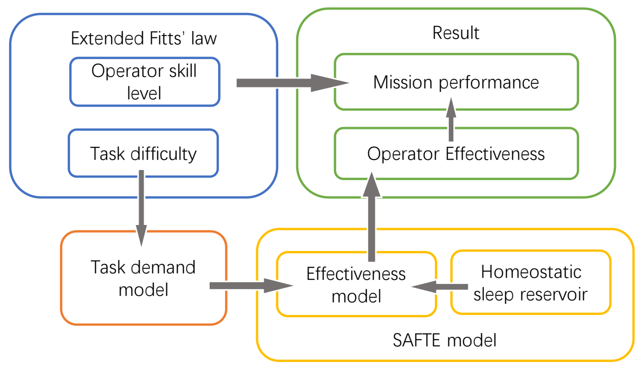

Fig. 1. Structure of the prediction model.

Human-robot teams are increasingly tasked with mission-critical operations, such as search and rescue, fire fighting, and Explosive Ordnance Disposal. Consequently, determining whether a human operator is fit for a mission and accurately predicting the mission's duration are crucial factors in the decision-making process. To address these concerns, we propose a performance prediction model that accounts for the cognitive effectiveness of robot operators by incorporating their fatigue levels. In particular, our model computes cognitive fatigue based on task demand and the homeostatic sleep condition, enabling the prediction of an operator's cognitive effectiveness.

The operator's effectiveness level can also be employed to enhance the human-robot team's performance prediction. Existing methods typically separate system performance and user experience into distinct evaluations [3], [4]. However, the fatigue of human operators can significantly impact the system's overall performance during missions. Therefore, integrating the cognitive effectiveness level with the operator's skill level is essential for accurately predicting human-robot team performance.

Our proposed model combines the Sleep, Activity, Fatigue, and Task Effectiveness (SAFTE) model [5] with the extended Fitts' Law [4], as depicted in Fig. 1. The SAFTE model integrates the homeostatic sleep process, circadian rhythm, and sleep inertia to generate a human's cognitive effectiveness. In

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this study, we first employ the task demand model, calculated using task difficulty derived from the extended Fitts' Law, to refine the cognitive effectiveness model by amplifying the attention capacity depletion rate based on task demand. The resulting effectiveness is then utilised to determine an operator's suitability for operating a robot. The operator's skill level is generated using standard tasks proposed within the extended Fitts' Law. By incorporating the operator's skill level, cognitive effectiveness, and mission requirements, mission performance (time) can be predicted with greater accuracy.

Our contribution to the field lies in the development of a novel performance prediction model that considers both the cognitive fatigue of human operators and their skill level, resulting in a more accurate representation of human-robot team performance. By employing the proposed model, stakeholders can make more informed decisions regarding mission assignments and optimise the efficiency and safety of mission-critical operations. Furthermore, this research sets the stage for future studies on the effects of fatigue on human-robot team performance, further enhancing the practicality and applicability of robotics in various domains.

This article is structured as follows. In Section II, we review related works in the fields of human-robot collaboration and human cognitive fatigue models. Next, Section III presents our proposed model for predicting task performance while accounting for cognitive fatigue. Subsequently, we provide a case study on a hypothetical scenario in Section IV to assess the effectiveness of our model, followed by a discussion of the results in Section V. Finally, we conclude the article in Section VI, summarising our findings and discussing potential future directions for this research area.

II. Related Works

A. Evaluation of Human-Robot Collaboration

Fully autonomous systems for open missions may not be feasible in the near future, thus necessitating efficient human-robot collaboration at various levels. Substantial efforts have been made over the years to advance human-robot collaboration [6], [7]. The development of new technologies and interfaces has led to the necessity of evaluating and predicting the performance of these collaborations for effective real-world mission applications. Some research focuses on evaluating the robot itself [8], while others concentrate on the interface side [9], [10]. Additionally, certain studies have attempted to incorporate human factors into the overall system performance evaluation [3], [4], [11], [12].

One study proposes a task-based framework, which considers successful and unsuccessful motions along with user opinions [11]. Other evaluation methods analyse the workload on participants in robot teleoperation using the NASA Task Load Index (NASA-TLX) and other customised scales [3], [4]. These scales provide a comprehensive view of user experience and workload, which can prove valuable in enhancing system design. Although workload plays a crucial role in system performance by inducing fatigue in human operators, few studies have investigated the impact of workload on human mental fatigue and performance in robot operation.

Accurate modelling of task difficulty is vital for predicting system performance in a given task. Task difficulty is directly related to the demand placed on a human operator and affects the fatigue accumulation rate during the task [13]–[17]. Consequently, a precise model for task difficulty is essential for both task performance modelling and fatigue modelling. In psychology, Fitts' Law [18] is a well-known tool for predicting human-computer system performance. It estimates the time required for tasks based on a task difficulty model. However, the original Fitts' Law is only one-dimensional, limiting its application outside human-computer interaction. Various modifications have been made to Fitts' Law, particularly concerning its task difficulty model. Some researchers have extended the task difficulty model to higher dimensions [19], [20]. Our previous study refines the task difficulty model to make it more suitable for robot teleoperation tasks [4]. However, to the best of our knowledge, no research has leveraged such task difficulty models to generate task demand and cognitive fatigue levels in human operators for robot teleoperation.

B. Modelling Human Fatigue

Fatigue is a significant factor affecting human performance in human-robot collaboration. Physical fatigue plays a crucial role in human-robot co-manipulation [21], while cognitive fatigue mainly influences human-robot teleoperation [22], [23].

1) Measurement-Based Approaches: Cognitive fatigue can be affected by numerous factors. Some research approaches fatigue estimation by continuously monitoring human and environmental activities [24]–[28]. A notable study provides a comprehensive model of human fatigue, incorporating numerous measured elements such as temperature, noise, circadian rhythms, and other environmental factors [24]. This model also accounts for the accumulative property of fatigue during tasks and proposes a dynamic fatigue detection model using Dynamic Bayesian Networks (DBN). Building on this work, various other fatigue detection models for driving in a dynamic manner have been developed, including those based on Hidden Markov Models (HMM) [25], DBN [26], and deep learning [27]. Although these models are comprehensive, they require a large amount of sensor data from both humans and the environment, which can be impractical for real-world mission applications.

2) Bio-mathematical Model: Bio-mathematical model approaches estimate human performance based on different schedules [29]. Due to the challenges in modelling neurophysiological mechanisms of human brain function and individual human differences, this approach uses average data from large volunteer group studies. One of the well-known bio-mathematical models is the SAFTE model and its application Fatigue Avoidance Scheduling Tool (FAST) [5], [30]. SAFTE employs sleep/wake schedules and the body's internal clock to predict changes in human cognitive performance. Some studies have improved the SAFTE model by considering additional parameters, including task demand, light countermeasures,

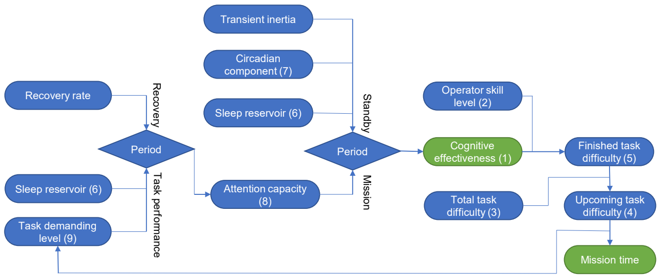


Fig. 2. Relationship of components with corresponding equation numbers in the model. Output Components are marked in green.

pharmaceutical countermeasures, night shifts, and jet lag, which significantly influence fatigue and human performance bio-mathematical models [31]–[33].

As robots become increasingly prevalent across various industries, humans operating robots under the influence of fatigue is an emerging concern. However, minimal research has considered fatigue in modelling human-robot collaboration [23]. Combining the current human-robot teleoperation model with these well-established bio-mathematical fatigue models can provide agencies with predictions of human performance under mental fatigue while operating robots.

III. Methodology

This study utilises the cognitive fatigue model based on the SAFTE model [5] and task demand [33] to predict cognitive effectiveness, E. The model also employs the extended Fitts' Law [4] to model task difficulty and to measure operator skill level. Subsequently, we integrate the influence of cognitive effectiveness on operator skills to provide a more precise prediction of system performance for a given mission, as shown in Fig. 2.

A. Modelling Cognitive Effectiveness

Although the SAFTE model includes both the waking and sleeping time, only the cognitive effectiveness during the waking time is considered in the proposed model. The waking time has two parts: the standby and mission periods. After the operator is awakened, the standby period starts immediately. The mission period starts when the operator starts to execute any mission. The cognitive effectiveness at time t, $E(t)$, of these two periods can be calculated as

$$E(t) = \begin{cases} R(t)/R_{\text{max}} + C_t - I_t, & \text{during standby} \\ E(t-1) - \frac{W_{\text{max}} - W(t)}{W_{\text{max}}}, & \text{during mission} \end{cases}, \quad (1)$$

where $R(t)/R_{\text{max}}$ represents the current ratio of sleep reservoir capacity from (6), and C_t is the circadian component from (7), I_t is the dimensionless transient inertia term at time t, as further explained in Section III-C, $W(t)$ is the current attention capacity with a maximum capacity of $W_{\text{max}} = 75$, as further explained in Section III-D.

This cognitive effectiveness represents the operator's performance level and can be used to evaluate if the operator will be suitable for executing the mission safely.

B. Task-Based Performance Prediction

The widely known Fitts' Law [18] predicts the performance of humans through task difficulty with the following equation:

$$PT = a + b \cdot ID, \quad (2)$$

where PT is the predicted task completion time, ID is the index of difficulty for the given task. Mathematically, b is the slope of PT over ID. Therefore, we understand b as the operator skill coefficient because it reflects the operator skill level through the changing ratio between task time and difficulty.

However, the original Fitts' Law models tasks in one-dimensional, which limits its application outside the screen. In [4], the task difficulty is extended to three-dimensional for real-world robot applications, which can be described as

$$ID_{\text{total}} = \sum_{1}^{n} ID_{\text{trans}_i} + ID_{\text{ori}_i} + ID_{\text{dir}_i}, \quad (3)$$

where ID_{trans_i}, ID_{ori_i}, and ID_{dir_i} represent the translation, orientation, and direction difficulty of the i-th motion step, respectively, please refer to [4] for detailed ID calculation.

In practical scenarios, the upcoming task difficulty diminishes as more motion steps are completed. Thus, the task difficulty left at time t has an Index of Difficulty, $ID_{\text{left}}(t)$, given by:

$$ID_{\text{left}}(t) = ID_{\text{total}} - ID_{\text{done}}(t-1), \quad (4)$$

where $ID_{\text{done}}(t-1)$ denotes the difficulty of motion steps and stages already completed at time t, which can be predicted through operator skill coefficient by

$$ID_{\text{done}}(t) = \frac{1}{b} \cdot E(t) \cdot \delta t, \quad (5)$$

where b is measured operator skill coefficient from Fitts' Law in (2).

With the predicted upcoming tasks, $ID_{\text{left}}(t)$, we can understand the estimated progress of the mission at the time t. Finally, iteration is used to predict if the operator can complete the mission within the safety limit of his/her cognitive effectiveness and how long the mission will take.

C. Awaking and Standby Period

In practical terms, cognitive fatigue largely depends on homeostatic sleep quality, which can be conceptualised as a sleep reservoir in the SAFTE Model. When the operator has had sufficient sleep and is in their optimal performance state, the homeostatic sleep reservoir capacity reaches its maximum, $R(t_0) = R_{\text{max}} = 2880$. During the initial 2 hours post-awakening, there is an immediate decline in performance due to the desynchrony between the rapid activation of the brain stem and the slower activation of the frontal cortical area [34], represented by transient inertia, I_t, with the maximum of 0.05. After this 2 hours period, the reservoir level at the current time t, $R(t)$, begins to deplete as follows:

$$R(t) = R(t-1) - V_k \delta t, \quad (6)$$

where $V_k = 30$ hour^{-1} is the depletion rate during wakefulness [33].

The circadian component, C_t, represents the body's internal clock and its influence on various physiological, which can be calculated by

$$C_t = c_t \cdot (a_1 + a_2 \frac{R_{\text{max}} - R(t)}{R_{\text{max}}}), \tag{7}$$

where $a_1 = 0.07$, $a_2 = 0.05$, and c_t is the circadian rhythm (c) arousal at time t, which varies between +1 and -1 [35].

D. Mission Period

While performing a mission, the depletion rate over time depends on the task demand and the sleep reservoir and its capacity. Much evidence has proven that higher cognitive demanding task donates a higher depletion rate on attention capacity [13]–[17]. Also, poor sleep quality contributes to the higher depletion rate [17], [36], [37]. Therefore, the current attention capacity, $W(t)$, can be expressed as

$$W(t) = W(t-1) + \dot{W}_t \delta t, \tag{8}$$

where

$$\dot{W}_t = \begin{cases} -\frac{R_{\text{max}}}{100+R(t)} \cdot L(t) \cdot V_d, & \text{during task performance} \\ V_r, & \text{during recovery} \end{cases},$$

is the current attention capacity at time t, $V_d = 1.14$ hour^{-1} is the depletion rate while performing tasks [38], $L(t)$ is the task demanding levels at time t, as explained below, R_t and R_{max} are homeostatic sleep reservoir from (6) and reservoir capacity, and $V_r = 11$ hour^{-1} is the recovery rate during resting [38].

The task demand level at time t, $L(t)$, refers to the cognitive attention required from the operator to perform the given task. This level is contingent upon task difficulty, whereby a more complex task necessitates greater cognitive attention and consequently has a higher task demand level.

Although a task may exhibit an unbounded level of difficulty when deemed infeasible, it is implausible for a task to impose infinite mental demand on the operator, even if the operator is aware that the task cannot be completed. To account for this, the model employs the following equation to map the task difficulty to the operator's mental demand level:

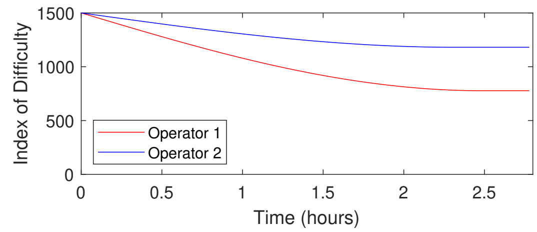
$$L(t) = \frac{\tan^{-1}(ID_{\text{left}}(t)/3600)}{\pi/6}, \tag{9}$$

where $L(t)$ represents the task demand levels at time t, with a range of $[0, 3]$ [33]. Since ID is measured according to the unit of seconds, $ID_{\text{left}}(t)$ is converted by $1/3600$ to fit with the rest of the parameters.

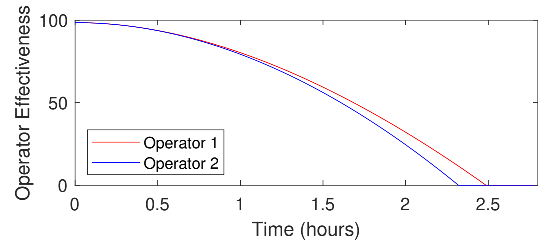
IV. Case Study and Results

To evaluate the feasibility of the proposed model, we designed a hypothetical scenario based on data from our prior human study on mobile manipulator teleoperation [4]. The scenario involves two human operators with average skill levels from groups A and B, as identified in the previous research. Group A comprises users with more teleoperation experience, while group B consists of users with less experience. Consequently, Operator 1, with the average skill level of group A, represents a more experienced user with a skill level of $b = 7.9$. Operator 2, with the average skill level of group B, represents a less experienced user with a skill level of $b = 17.0$.

Both operators are required to perform the same mobile manipulator teleoperation mission, which has a total difficulty of 1500 ($ID_{\text{total}} = 1500$) and consists of three sub-tasks, each with a difficulty of 500 ($ID_i = 500$), as shown in Table I. The field commander needs to know whether the operators can complete the mission and the estimated time required for each operator.



(a) Total upcoming task difficulty over time



(b) Effectiveness over time

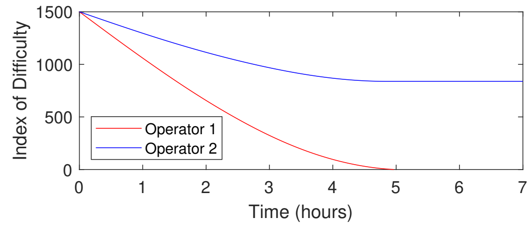
Fig. 3. In the situation of both operators performing the whole mission continuously, the upcoming task difficulty and current operator effectiveness in task performance at the current time are shown in the graph. 0 upcoming task difficulty means all task has been completed, and 0 effectiveness means the operator is no longer suitable for a mission.

TABLE I
Parameters used in the case study, with calculated values in bold. All parameters are dimensionless.

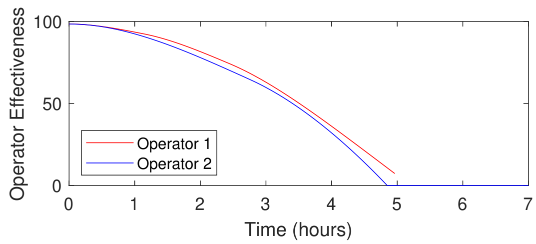
Parameters	ID_{total}	ID_i	$R(t)$	I_t	c_t	$\mathbf{C_t}$	$\mathbf{E(t_0)}$
Value	1500	500	2880	0.05	0.5	**0.035**	**98.5%**

A. Standby Period

We assume that both operators arrive at work in reasonably good homeostatic sleep conditions for the scenario. Specifically, they have a night of sufficient sleep before the mission ($R(t) = R_{\text{max}} = 2880$). However, as employees typically do not start working immediately upon waking up, both operators begin the mission 2 hours after awakening ($I_t = 0.05$) and have a circadian rhythm of 0.5 at this time ($c_t = 0.5$). Consequently, by using (7), the circadian component at this time can be calculated as $C_t = 0.035$. Then, with all the necessary information, the effectiveness at the start of the

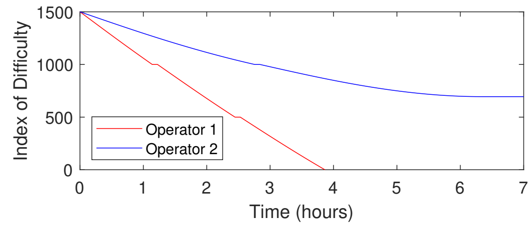


(a) Total upcoming task difficulty over time

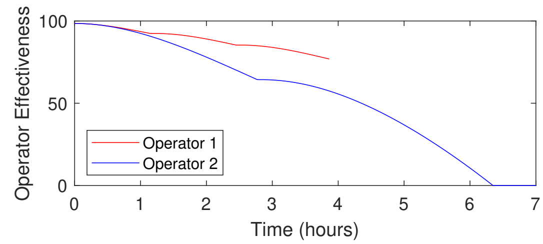


(b) Effectiveness over time

Fig. 4. In the situation of the mission being split into 3 sub-tasks without resting time in between, the upcoming task difficulty and current operator effectiveness in task performance at the current time are shown in the graph.



(a) Total upcoming task difficulty over time



(b) Effectiveness over time

Fig. 5. In the situation of the mission being split into 3 sub-tasks and having resting time in between, the upcoming task difficulty and current operator effectiveness in task performance at the current time are shown in the graph.

mission can be obtained from (1), yielding $E(t_0) = 98.5\%$, as shown in Table I.

B. Executing Mission as a Whole

To predict the performance of the two operators, we apply the proposed model to the mission. Initially, we assume they perform the entire mission without stopping or dividing it. The results indicate that neither operator can complete the mission due to fatigue accumulation, with both operators reaching 0 cognitive effectiveness and becoming unsuitable for operation before the mission is completed, as shown in Fig. 3. From Fig. 3(b), Operator 1 and 2 have their effectiveness reaches 0 at $t = 2.49$ hours and $t = 2.32$ hours.

C. Dividing Mission without Resting

In the third approach, the agency divides the mission into three sub-tasks, incorporating a 5-minute rest period between each subtask to facilitate recovery of the operators' attention capacity, which leads to improved performance, as depicted in Fig. 4. Operator 1 accomplishes the mission at $t = 3.86$ hours, with a remaining effectiveness of $E_{\text{end}} = 76.91\%$. However, Operator 2 is unable to complete the mission and reaches zero effectiveness at $t = 6.45$ hours.

D. Division of Mission with Rest Periods

In the third approach, the agency splits the mission into three sub-tasks. It also gives the operators 5 minutes of rest between each subtask to recover their attention capacity leading to a better result, as shown in Fig. 5. Operator 1 completes the mission at $t = 3.86$ hours, with the remaining effectiveness at $E_{\text{end}} = 76.91\%$. However, Operator 2 is still unable to finish the mission and reaches 0 effectiveness at $t = 6.45$ hours.

V. Discussion

The comparison of Fig. 3, Fig. 4, and Fig. 5 indicates that partitioning a larger mission into smaller sub-tasks renders the otherwise unfeasible mission achievable, while incorporating rest periods further enhances human performance. The model elucidates this phenomenon by demonstrating that dividing a larger mission reduces the task demand on the operator, resulting in a decrease in the rate of attention capacity depletion. When the attention capacity is depleted at a slower pace, its impact on cognitive effectiveness is less pronounced. This mirrors real-world scenarios, where substituting a complex mission with several less complicated sub-tasks diminishes the volume of information to be processed and work to be planned for the operator at a given time.

Fig. 4 also reveals that, upon dividing the mission, Operator 1 can complete the mission with the highest remaining effectiveness ($E_{\text{end}} = 76.91\%$). Nonetheless, Operator 2 is still unable to finish the mission before their effectiveness drops to 0. This outcome mirrors real-world situations where operators possessing higher skill levels can tackle more challenging tasks compared to their less-skilled counterparts. Moreover, as depicted in Fig. 4 and Fig. 5, brief rest periods further boost performance by offering recovery intervals. These recovery intervals enable operators to recuperate from accumulated fatigue, thereby better preparing them for subsequent tasks. This is evident from Fig. 4(b), where the operators regain their attention capacity during the 5-minute break, and following the break, their cognitive effectiveness resumes at a new, reduced rate of decline. Consequently, the results suggest that organising a demanding mission into more manageable sub-tasks and allotting rest periods for operators to recover their attention capacity is advantageous.

VI. Conclusion

This study introduced a human-robot collaboration performance model centred on operator skill level and fatigue accumulation for a specified mission. The model extends Fitts' Law [4] to represent task difficulty and operator skill level, while the SAFTE model [5] is employed to account for fatigue accumulation and its impact on the operator. As such, the model can predict an operator's cognitive effectiveness to assess their suitability for a mission and the duration required for mission completion. Furthermore, the model takes recovery periods into account, enabling the agency to better strategise mission planning and enhance performance.

Given that the influence of fatigue on human-robot collaboration remains an emerging area of research, many of the model's elements and coefficients are derived from studies in related fields, such as transportation and mechanical operation. Future investigations will concentrate on measuring these elements within human-robot interactions to refine the model's accuracy. Additionally, in the case study, the operator is considered unsuitable for executing missions when their effectiveness falls to zero. In real-world applications, a more stringent evaluation involving a higher cut-off for operator effectiveness would be imposed as a safety precaution, particularly in high-risk missions.

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