# Case Study – Modeling Human Fighter Pilot Performance

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**Abstract.** The study of human fighter pilot performance explores what affects the performance of fighter pilots during missions. This case study investigates the relationship between physical, psychological, and environmental factors that influence pilot performance. By analyzing key input features such as heart rate, sleep quality, mission complexity, experience level, and environmental conditions, we aim to identify the variables that significantly impact cognitive load, and stress levels. Understanding these factors will help to improve pilot's training, mission planning, and determine whether their conditions are allowed to fly on the day.

**Keywords:** Pilot's Performance, Modelling and Simulation, Temporal Dynamics

## 1 Introduction

This study examines how various factors influence human fighter pilot performance, a key element in the success of military missions. Fighter pilots operate high-speed jets under extreme conditions, where their physical and mental skills are tested to the limit. Their performance is influenced by factors such as physical fatigue, cognitive load, stress level, environmental conditions, and the pilot's experience and training. Understanding and improving these factors is crucial for enhancing pilot performance and mission success.

This case study aims to develop and create a model that captures the key input features that affect fighter pilot performance. By representing these factors mathematically and simulating different scenarios, we can understand how pilots perform under various conditions. This model will help improve training programs, mission planning and support systems, making pilots become more effective and safer.

Generally, this study is separated into four parts. First, the key factors that affect the pilot performance are identified and a conceptual model is developed to represent the relationship between the factors. After that, mathematical equations are created to represent the interplay between these factors. Second, we implemented a model in the octave and created some simulations scenarios. The simulation results are then analyzed. Third, the model's accuracy is then evaluated by using the p-value test. Finally, practical applications of the model developed are explored, including training methods and the use of wearable technology to collect data.

By examining these aspects, this study aims to enhance the understanding of fighter pilot performance and improve training and support systems for pilots in stressful situations.

## 1.1 Variable

Variables:

| Variable | Description | Additional info | Symbol |
|---|---|---|---|
| Heart Rate | An indicator to measure the pilot's physical stress level in beats per minute. | High HR = High SL | HR |
| Sleep Quality | Pilot's sleep quality before the mission affect significantly on their performance. | Low SQ = High CL and Low RT | SQ |
| Mission Complexity | Represents the difficulty of the mission. | High MC = High CL and High SL | MC |
| Environmental Stressor | Refers to adverse weather conditions such as sunny day rainy day, strong winds, or low visibility. | High ES = High CL and High SL | ES |
| Cognitive Load | Mental's effort required for the mission. | High CL = Low SA | CL |
| Short-Term Stress Level | Refers to immediate stress experienced by the pilot during the mission. | | $SL_s$ |
| Physical Fatigue | Physical tiredness of the pilot experienced will directly affect their flying performance. | High PF = Low P | PF |
| Reaction Time | Higher reaction time indicate the pilot's speed to respond to something is faster. | High RT = High P | RT |
| Situational Awareness | Pilot's ability to perceive and understand their environment. | High SA = High P | SA |
| Experienced Level | The number of years the pilot has been flying. | | EL |
| Short-Term Performance | Pilot's performance furing a specific mission or short period. | | $P_s$ |
| Long-Term Stress Level | Accumulated Short-term Stress level experienced by the pilot over a long period. | | $SL_L$ |
| Long-Term Performance | Accumulated Performance over a long period. | | $P_L$ |

**Table 1.1.** Variable definitions

## 2 Background

The study of fighter pilot performance aims to understand how factors such as heart rate, sleep quality, mission complexity, experience level and environmental conditions affect a pilot's cognitive load, stress levels, physical fatigue, situational awareness, reaction time and overall performance during missions. The goal is to optimize training programs, mission planning, and support systems to enhance pilots; ability to manage the intense demands of their roles and improve mission success rates. This study is interdisciplinary, incorporating insights from psychology, physiology, aviation medicine, and cognitive science to provide a comprehensive understanding of how various elements influence, ultimately leading to better training and support strategies for fighter pilots.

## 3 Formal Model

This section will explain the details of the model from a mathematical point of view. The model is complex with a total of 13 nodes interconnecting to one another. The model in question can be seen in **Fig. 3.1.** and **Table 3.1**.

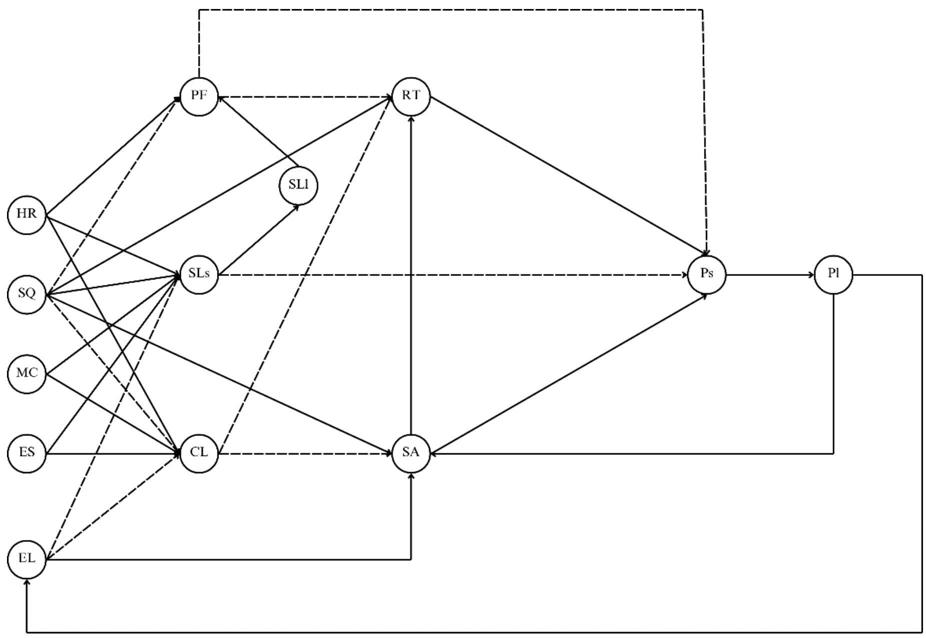


**Fig. 3.1.** Relation Diagram of the Model

*Solid line indicates a positive relationship, Dashed line indicates a negative relationship

| | HR | SQ | MC | ES | EL | PF | $SL_s$ | $SL_L$ | CL | RT | SA | $P_s$ | $P_L$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **HR** | | | | | | + | + | | + | | | | |
| **SQ** | | | | | | - | - | | - | + | + | | |
| **MC** | | | | | | | + | | + | | | | |
| **ES** | | | | | | | + | | + | | | | |
| **EL** | | | | | | | - | | - | | + | | |
| **PF** | | | | | | | | | | | | - | |
| $SL_s$ | | | | | | | | + | | | | - | |
| $SL_L$ | | | | | | + | | | | | | | |
| **CL** | | | | | | | | | | - | | | |
| **RT** | | | | | | | | | | | | + | |
| **SA** | | | | | | | | | | | | + | |
| $P_s$ | | | | | | | | | | | | | + |
| $P_L$ | | | | | + | | | | | | + | | |

**Table 3.1.** Relationship Matrix of the Model

The relationships between the nodes have been determined based on previous literature, therefore the model is formed. All nodes are designed to only accept input and produce outputs that range from 0 (low) to 1 (high) to reduce the model's complexity. The model is split into two relation types: instantaneous and temporal relations.

## 3.1 Instantaneous Relationships

In this model, there are 5 different inputs: Heart Rate (HR), Sleep Quality (SQ), Mission Complexity (MC), Environmental Stressor (ES), and Experienced Level (EL). For further explanation, SQ and EL are seen as positive where the higher the value of SQ and EL of a pilot, the better that pilot performs at that time. On the other hand, HR, MC and ES are seen as negative where the higher the value, the higher the influence on the pilot's performance.

Other than the five input nodes, there are a total of 7 other instantaneous relationships that are present. They are Cognitive Load (CL), Short-Term Stress Level (SLs), Physical Fatigue (PF), Reaction Time (RT), Situational Awareness (SA), and Short-Term Performance (Ps).

$$CL(t) = \left(1 - \alpha_{CL} EL(t)\right)\left[\left( \omega_{CL_1} MC(t) + \omega_{CL_2} ES(t) + \omega_{CL_3} HR(t)\right) - \beta_{CL} SQ(t)\right]$$

The equation for Cognitive Load (CL) at time t calculates the mental effort required by the pilot. It considers MC, ES, and HR as factors that increase the CL, each weighted by parameters $\omega_{CL_1}$, $\omega_{CL_2}$, and $\omega_{CL_3}$ respectively. Sleep Quality (SQ) reduces the CL, scaled by $\beta_{CL}$. The pilot's experience level (EL) also reduces the overall cognitive load, scaled by $\alpha_{CL}$. Higher values of EL and SQ lower the cognitive load, while higher MC, ES, and HR increase it.

$$SL_s(t) = ([\omega_{SLs_1} HR(t) + \omega_{SLs_2} ES(t) + \omega_{SLs_3} MC(t)] - \lambda_{SLs} SQ(t))\left(1 - \alpha_{SLs} EL(t)\right)$$

Short-Term Stress Level (SLs) at time *t* is determined by Heart Rate (HR), Environmental Stressor (ES), and Mission Complexity (MC), with weights respectively. Higher HR, ES, and MC increase SLs. However, SLs is moderated by Experienced Level (EL) and Sleep Quality (SQ). Both EL and SQ have a reducing effect on SLs, indicating that higher values of EL and SQ significantly lower the stress levels.

$$PF(t) = \alpha_{PF}[\omega_{PF_1} HR(t) + \omega_{PF_2}(1 - SQ(t))] + (1 - \alpha_{PF})(SL_L(t-1))$$

Physical Fatigue (PF) at time *t* is influenced by Heart Rate (HR) and Sleep Quality (SQ). The parameter $\boldsymbol{\alpha_{PF}}$ balances the contributions of these immediate factors and Long-Term Stress Level ($\boldsymbol{SL_L}$). High HR and low SQ increase PF, with weights scaling their effects. The term $(\mathbf{1} - \boldsymbol{\alpha_{PF}})$ indicates the influence of $\boldsymbol{SL_L}$ on PF.

$$RT(t) = \gamma_{RT}(\omega_{RT_1} SQ(t) + \omega_{RT_2} SA(t)) + (1 - \gamma_{RT})(1 - (\omega_{RT_3} CL(t) + \omega_{RT_4} PF(t)))$$

Reaction Time (RT) at time t is positively influenced by Sleep Quality (SQ) and Situational Awareness (SA), with their effects weighted by $\boldsymbol{\omega_{RT_1}}$and $\boldsymbol{\omega_{RT_2}}$ respectively. The parameter $\boldsymbol{\gamma_{RT}}$ determines how much these positive factors contribute to RT. Conversely, RT is negatively impacted by Cognitive Load (CL) and Physical Fatigue (PF), weighted by $\boldsymbol{\omega_{RT_3}}$ and $\boldsymbol{\omega_{RT_4}}$. The term $(\mathbf{1} - \boldsymbol{\gamma_{RT}})$ balances the negative influences. Essentially, better sleep quality and situational awareness improve reaction time, while higher cognitive load and physical fatigue slow it down.

$$SA(t) = \beta_{SA}\left[\omega_{SA_1} SQ(t) + \omega_{SA_2} EL(t) + \omega_{SA_3} P_L(t-1)\right] + (1 - \beta_{SA})(1 - CL(t))$$

Situational Awareness (SA) at time *t* is positively influenced by Sleep Quality (SQ), Experienced Level (EL), and Long-Term Performance (Pl) from the previous time step, with their effects weighted by $\boldsymbol{\omega_{SA_1}}$, $\boldsymbol{\omega_{SA_2}}$, and $\boldsymbol{\omega_{SA_3}}$respectively. The parameter $\boldsymbol{\beta_{SA}}$ determines the overall contribution of these positive factors. On the other hand, SA is negatively impacted by Cognitive Load (CL). The term $(\mathbf{1} - \boldsymbol{\beta_{SA}})$ balances this negative influence, indicating that higher CL reduces situational awareness. Essentially, better sleep quality, higher experience levels, and improved long-term performance enhance situational awareness, while higher cognitive load reduces it.

$$EL(t) = \delta_{EL} EL_{base}(t) + (1 - \delta_{EL})(P_l(t-1))$$

Experienced Level (EL) at time $t$ is a combination of the base experienced level $EL_{base}$ and the previous Long-Term Performance ($P_l(t-1)$). The parameter is used to determine the weighting between these two components. Essentially, EL is updated based on a pilot's inherent experience level and their recent performance, with past performance influencing future experience.

$$P_s(t) = \eta_{Ps}\left(\omega_{Ps_1} SA(t) + \omega_{Ps_2} RT(t)\right) + (1 - \eta_{Ps})(1 - (\omega_{Ps_3} SLs(t) + \omega_{Ps_4} PF(t)))$$

Short-Term Performance (Ps) at time $t$ is positively affected by Situational Awareness (SA) and Reaction Time (RT), with their contributions weighted by $\omega_{Ps_1}$ and $\omega_{Ps_2}$ respectively. The parameter $\eta_{Ps}$ determines the overall impact of these positive influences. On the other hand, Ps is negatively impacted by Short-Term Stress Level ($SL_S$) and Physical Fatigue (PF), with their effects weighted by $\omega_{Ps_3}$ and $\omega_{Ps_4}$. The term $(1 - \eta_{Ps})$ scales these negative factors. Essentially, better situational awareness and quicker reaction times enhance short-term performance, while higher stress and physical fatigue reduce it. This equation captures the complex interplay between these variables, determining the pilot's immediate performance.

### 3.2 Temporal Relationships

$$SL_L(t + \Delta t) = SL_L(t) + [SL_s(t) - SL_L(t)] \cdot \Delta t$$

Long-Term Stress Level ($SL_L$) at time $t + \Delta t$ evolves based on the current Short-Term Stress Level ($SL_s$) and the existing $SL_L$. The difference between $SL_s$ and $SL_L$ is scaled by $\Delta t$, determining the rate of change. If $SL_s$ is higher than $SL_L$, the long-term stress increases, and vice versa.

$$P_L(t + \Delta t) = P_L(t) + [P_s(t) - P_L(t)] \cdot \Delta t$$

Long-Term Performance ($P_L$) at time $t + \Delta t$ evolves based on the current Short-Term Performance ($P_S$) and the existing $P_L$. The difference between $P_S$ and $P_L$) is scaled by $\Delta t$, which determines the rate of change. If $P_S$ is higher than $P_L$, the long-term performance increases, and vice versa. This ensures that $P_L$ gradually adjusts toward the current short-term performance level over time.

# 4 SIMULATION RESULTS

| Agent/ Performance | Heart Rate (HR) | Sleep Quality (SQ) | Experienced Levels (EL) | Mission Complexity (MC) | Environmental Stressor (Es) |
|---|---|---|---|---|---|
| 1 High | 0.1 | 0.9 | 0.9 | 0.1 | 0 |
| 2 Low | 0.9 | 0.1 | 0.1 | 0.9 | 1 |
| 3 Moderate | 0.5 | 0.1 | 1 | 0.9 | 0 |
| 4 M-L | 0.1 | 0.1 | 1 | 0.9 | 0 |
| 5 M-H | 0.9 | 0.9 | 0.1 | 0.1 | 0 |
| 6 Moderate | 0.5 | 0.9 | 0.5 | 0.9 | 1 |

**Table. 4.1.** The table shows the values for each variable for six scenarios.

**Case#1:**

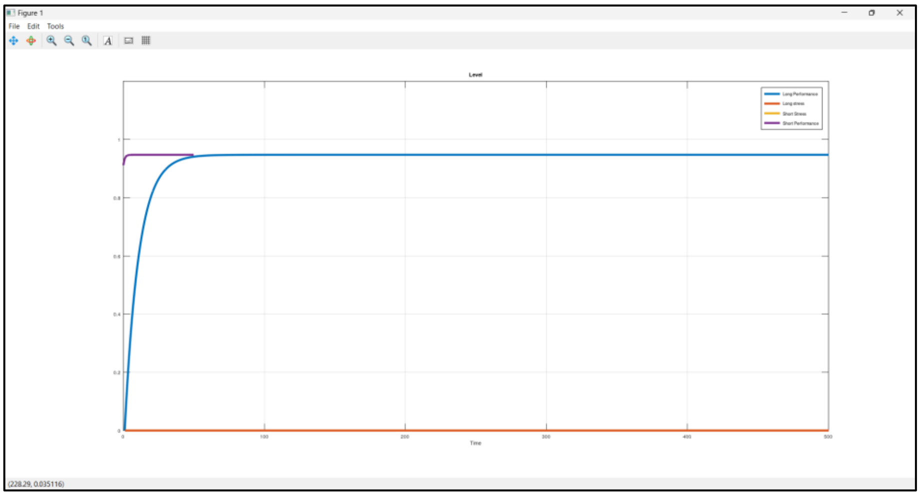


**Fig. 4.1.** In this scenario, initially, the pilot's short-term performance (Ps) is high due to good sleep quality and low stress, which positively influences the long-term performance (Pl) as the good sleep quality will increase the reaction time and situational awareness of the pilot. Over time, the long-term performance stabilizes and reaches its equilibrium state. This flattening indicates that the pilot is performing at their best under good conditions and there are no significant changes in the influencing factors.

The long-term stress starts at zero as shown in the graph above as the initial condition (low HR, high SQ, low MC, and no ES) contributes to very low short-term stress (SLs), which in turn keeps the long-term stress low. As time progresses, the short-term stress remains low due to the stable and good conditions, preventing any accumulation of long-term stress. The long-term stress (SLl) quickly reaches zero and remains at there, which indicates that the pilot is not experiencing any significant stress over the mission duration.

Overall, the graph reflects a scenario where the pilot is operating under optimal conditions which are low stress and high performance. The long-term performance graph shows an initial increase followed by stabilization, which indicates that the pilot can maintain peak performance. The long-term stress graph starts and ends at zero, showing that the pilot does not accumulate significant stress, which is ideal for mission success.

**Case#2:**

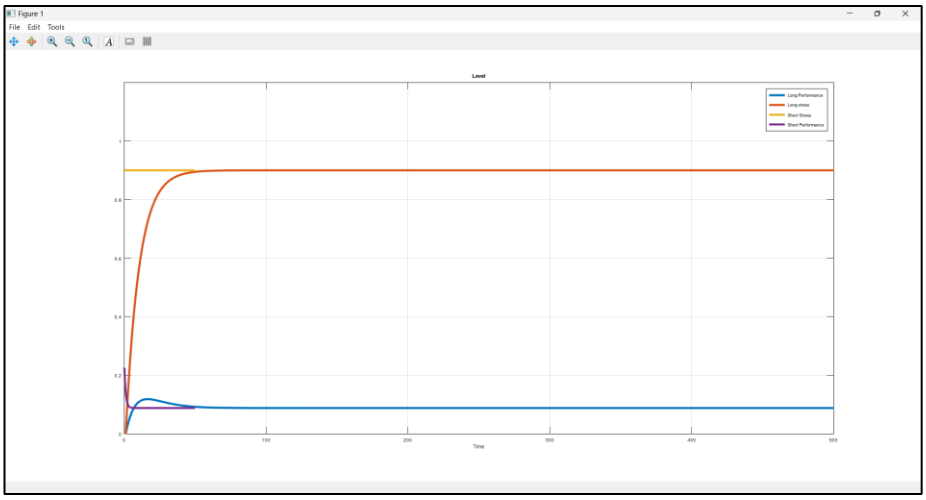


**Fig. 4.2.** In this scenario, the high heart rate indicates the pilot is very nervous and low sleep quality indicates that the pilot is fatigued, reducing their ability to perform complex tasks effectively. The pilot also lacks experience to handle stress and complex tasks well. High mission complexity in this situation will add to the pilot's cognitive load and stress level while poor environmental conditions make the mission become even more challenging, thus increasing stress and reducing performance.

Initially the long-term performance curve increases, this might be due to the reason that the pilot initially puts in some effort, causing a slight increase in the performance. However, the combined effects of high stress, fatigue, lack of experience, and complex mission conditions cause the performance to drop. The performance level of the pilot stabilizes at a lower point as the pilot adjusts to the stress but can't perform well due to the difficult conditions, physical fatigue and lack of experience.

Due to the challenging conditions, the pilot's short-term stress is high and causes the long-term stress level to rise quickly. After the rapid increase, the long-term stress levels stabilized but remain high due to the continuous pressure from the mission and poor environmental conditions.

The pilot's high stress and fatigue, combined with their lack of experience, high mission complexity and bad environment conditions, cause their performance to initially improve slightly but then decline and stabilize at a lower level. The stress level rises quickly and remains high, showing that the pilot struggles significantly throughout the mission.

**Case#3:**

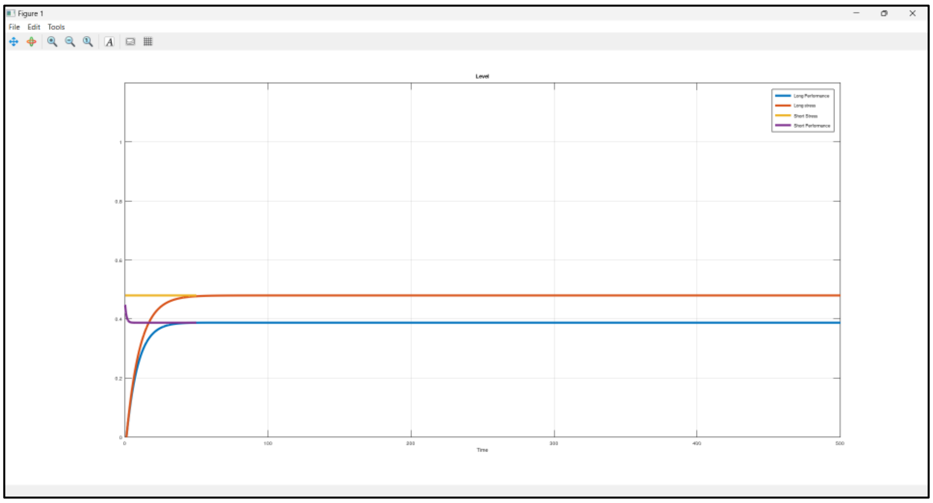


**Fig. 4.3.** n this scenario, the pilot has a moderate heart rate, indicating they are in a balanced physical state. However, the pilot has low sleep quality (SQ = 0.1), meaning they are quite fatigued. However, the pilot has a high experience level (EL = 1), which helps them manage the complex mission (MC = 0.9). Additionally, the environmental conditions are good (ES = 0), which reduces stress.

From the graph, the long-term performance curve shows that it increases initially and then stabilizes at 0.4. This initial rise happens because the pilot's high experience helps them deal with the mission's complexity and opposes their poor sleep quality. Over time, their performance levels stabilized at 0.4, showing that experience helps them keep a moderate performance despite the challenging mission and lack of sleep.

On the other hand, the long-term stress curve shows a fast increase at the beginning. This quick rise in stress is due to the high mission complexity and low sleep quality, which puts a lot of stress on the pilot. Eventually, the stress levels stabilize at 0.5, which is higher than the performance level. This higher stress level means the pilot continues to feel the effects of the tough mission and their fatigue, even though the good environmental conditions help reduce some stress.

Overall, the long-term stress levels rise quickly due to the mission's complexity and poor sleep quality, stabilizing at a higher level (0.5). However, the pilot's high experience level and the good environmental conditions helps them to handle the complex mission, leading to an increase and then stabilization of performance at a moderate level (0.4).

**Case#4:**

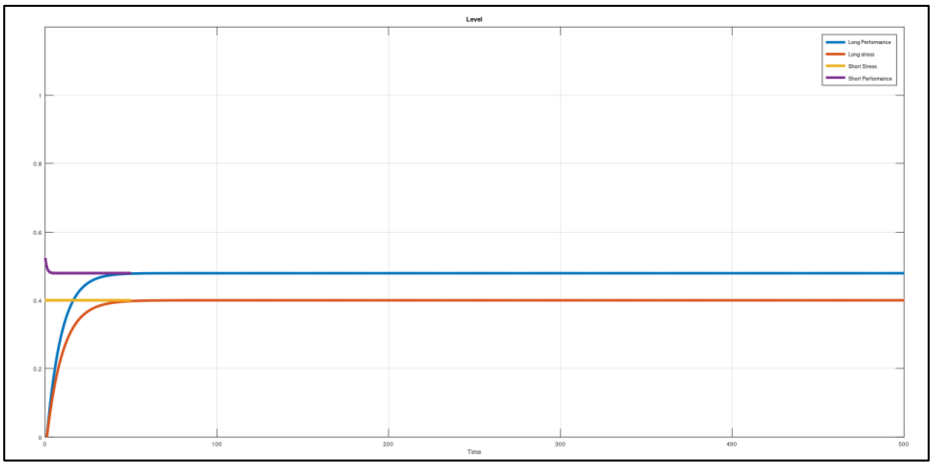


**Fig. 4.4.** In this scenario, the pilot has a low heart rate (HR), indicating stable emotions. Despite this, the pilot has had poor sleep quality (SQ) and is undertaking a highly complex mission. However, the pilot's high experience level (EL) and favorable environmental stressors (ES), like good weather conditions, play a significant role in moderating stress levels.

The graphs show that the pilot experiences moderate stress, primarily due to poor sleep quality and the complexity of the mission. Poor sleep quality affects physical fatigue, which can contribute to higher stress levels. Nevertheless, the pilot's extensive experience and the good environmental conditions help manage and control this stress effectively.

Initially, the pilot's short-term performance dips slightly due to the combined impact of poor sleep and the challenging mission. However, due to their high experience level, the pilot quickly adapts, and their performance stabilizes over time. This ability to adapt showcases the importance of experience in managing complex situations and maintaining performance levels even when other factors, like sleep quality, are poor than ideal.

Overall, the performance of the pilot is moderate low compared to other graphs and the stress level is also handled in a moderate pace.

**Case#5:**

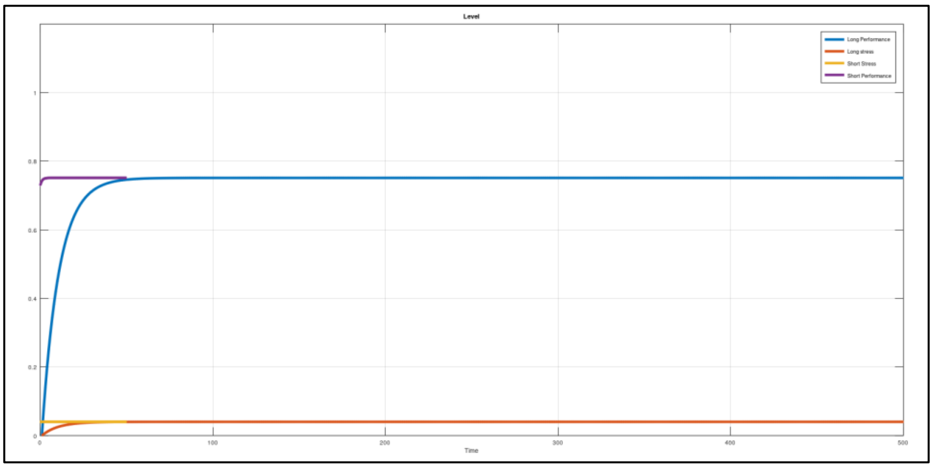


**Fig. 4.5.** In this scenario, the pilot's high heart rate (HR), showing they are experiencing nervous emotions. Despite this, the pilot benefits from good sleep quality (SQ) and is engaged in a simple mission. However, their low experience level (EL) and the presence of unfavorable environmental stressors (ES), such as bad weather conditions, could potentially influence their performance.

The graphs illustrate that the pilot experiences less stress, primarily due to the good sleep quality and the simplicity of the mission. Quality sleep is crucial as it helps in controlling physical fatigue over time. When individuals receive adequate sleep, they are less likely to experience physical exhaustion quickly, enabling them to maintain focus during the mission.

Given that the mission is relatively simple and the pilot has had sufficient rest, their performance remains at a moderate to high level. The poor weather conditions and elevated heart rate do not significantly impact their stress level or performance. This indicates that the beneficial effects of good sleep quality and the simplicity of the mission outweigh the negative influences of unfavorable environmental stressors and the pilot's nervous emotions.

**Case#6:**

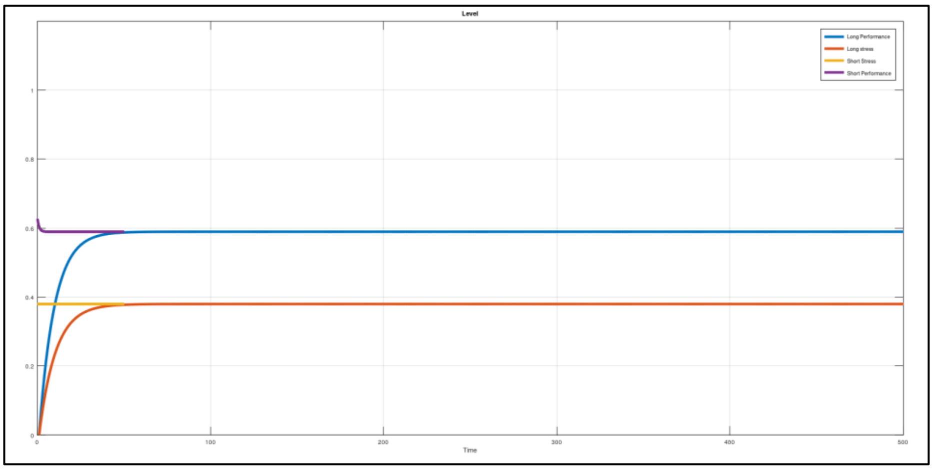


**Fig. 4.6.** In this scenario, the pilot has a moderate heart rate, indicating a balanced state—not too relaxed but not overly stressed either. The pilot has had good sleep quality and is tackling a highly complex mission. With a moderate level of experience and facing poor weather conditions, the pilot's performance is moderate, and they are experiencing moderate to low stress.

The graphs show that the pilot is dealing with a moderate level of stress, primarily due to the complexity of the mission and the adverse weather. The pilot’s experience level is not quite up to par with the demands of such a complex mission.

Overall, while the pilot is managing, the challenges posed by the mission's complexity and poor weather conditions are evident. The good sleep quality helps, but the mismatch between the pilot’s experience and the mission's demands is a significant factor too in the moderate stress levels observed.

# 5 Evaluation

## 5.1 Techniques to Verify the Correctness of the Model

To ensure the correctness of the mathematical model and its implementation, several verification techniques were employed. These techniques are crucial for confirming that the model accurately represents the intended system and behaves as expected under various conditions.

### 5.1.1 Mathematical Analysis

To verify the correctness of our mathematical model, we performed a mathematical analysis by substituting the steady-state values obtained from simulations into the model equations. This method involves ensuring that the model's equilibrium states are consistent with its theoretical predictions.

We began by analyzing the equation for short-term performance $\boldsymbol{P_s(t)}$:

$$\boldsymbol{P_s(t) = \eta_{Ps}\left( \omega_{Ps_1}SA(t) + \omega_{Ps_2}RT(t)\right) + (1-\eta_{Ps})(1-( \omega_{Ps_3}SLs(t) + \omega_{Ps_4}PF(t)))}$$

We then looked at the equation for long-term performance $\boldsymbol{P_L(t+\Delta t)}$:

$$\boldsymbol{P_L(t+\Delta t) = P_L(t) + [P_s(t) - P_L(t)] \cdot \Delta t}$$

By combining the two equations:

$$\boldsymbol{P_L(t+\Delta t) = P_L(t) + \left[\eta_{Ps}\left( \omega_{Ps_1}SA(t) + \omega_{Ps_2}RT(t)\right) + (1-\eta_{Ps})(1-( \omega_{Ps_3}SLs(t) + \omega_{Ps_4}PF(t))) - P_L(t)\right] \cdot \Delta t}$$

The equation expressing that a state of $P_L$ is stationary at time t is:

$$\boldsymbol{P_L(t) = \eta_{Ps}\left( \omega_{Ps_1}SA(t) + \omega_{Ps_2}RT(t)\right) + (1-\eta_{Ps})(1-( \omega_{Ps_3}SLs(t) + \omega_{Ps_4}PF(t)))}$$

The steady-state values (at time step t = 500) obtained from the simulation are as follows:

| Variable/Parameter | Values |
|---|---|
| Heart Rate (HR) | 0.625 |
| Sleep Quality (SQ) | 0.444 |
| Mission Complexity (MC) | 0.778 |
| Experience Level baseline (EL_base) | 0.4 |
| Environmental Stressor (ES) | 0.444 |
| Situational Awareness (SA) | 0.3886 |
| Reaction Time (RT) | 0.354 |
| Short term Stress level (SLs) | 0.4987 |
| Physical Fatigue | 0.5446 |
| Long term performance (Pl) | 0.42483 |
| Short term performance (Ps) | 0.42483 |
| $\eta_{Ps}$ | 0.5 |
| $\omega_{Ps_1}$ | 0.5 |
| $\omega_{Ps_2}$ | 0.5 |
| $\omega_{Ps_3}$ | 0.5 |
| $\omega_{Ps_4}$ | 0.5 |

**Table. 5.1.1.** The table shows the steady-state values for each variable at the time step $t = 500$.

Using the steady-state values from the simulation and substituting all the values into the equation.

$$\boldsymbol{P_l(t)} = \mathbf{0.5(0.5 * 0.3886 + 0.5 * 0.354) + (1 - 0.5)(1 - (0.5 * 0.4987 + 0.5 * 0.5446))}$$

$$\boldsymbol{P_l(t)} = \mathbf{0.424825}$$

We compared this calculated value and the actual value obtained from the simulation:

**Actual value – Calculated Value = 0.42483 – 0.424825 = 0.000005**

Since the difference between the actual performance value and the calculated performance is less than $10^{-3}$, therefore this gives the evidence that the model as implemented indeed does what it was meant to do.

If the $P_L$ at equilibrium is the same as the $P_S$ from the simulation, it shows that the model accurately reflects how a pilot's performance changes over time. In the real-world application, when $P_L$ is verified, it means the model can reliably predict how a pilot's performance will evolve. This is crucial for planning training and career development. For instance, if a pilot consistently performs well, they might be considered for advanced training. On the other hand, if their performance declines, the model can help identify the need for additional support or training. This ensures that pilots receive the appropriate guidance and resources to maintain or improve their performance.

### 5.1.2 Unit Testing

As we know, unit Testing is evaluated to ensure that each component of the model functions correctly in isolation. In this step, we would initialize a worst case for the variables. The initial values for the variables are shown below.

| Variable | Values |
|---|---|
| Heart Rate (HR) | 0.80 |
| Sleep Quality (SQ) | 0.05 |
| Mission Complexity (MC) | 0.85 |
| Experience Level baseline (EL_base) | 0.10 |
| Environmental Stressor (ES) | 0.88 |

**Table. 5.1.2.** The table shows the values for each variable to represent the worst case.

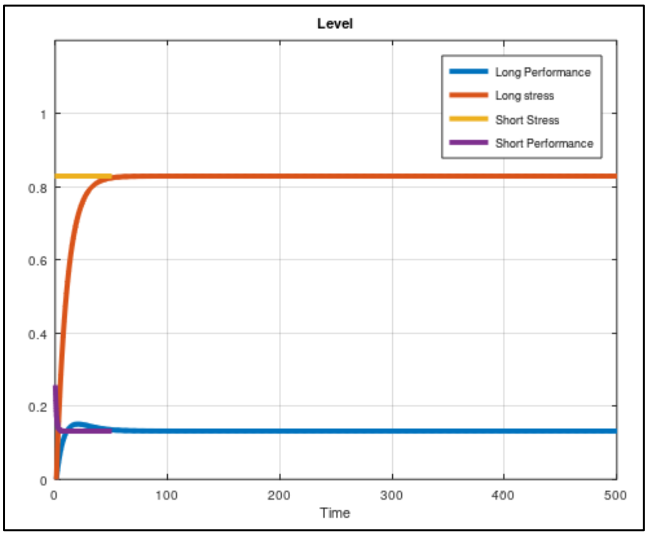


**Fig. 5.1.** This figure illustrates the worst-case scenario characterized by a high heart rate, high mission complexity, high environmental stressor, low sleep quality, and low experience level.

Under these conditions, the model shows that the stress level is extremely high, higher than 80%, while the performance is extremely low, which is lower than 20%. Hence, we can prove that our model accurately captures the inverse relationship between stress levels and performance, and it validates the correctness of the equations representing these dynamics. Specifically, as stressors increase and mitigating factors like sleep quality and experience decrease, the model appropriately reflects the expected rise in stress and the corresponding drop in performance.

### 5.1.3 Integration Testing

While for integration testing, it focuses on evaluating the interactions between different components of the model to ensure they work together as expected. In this step, we know that Heart Rate (HR), Sleep Quality (SQ), Mission Complexity (MC), Environmental Stressor (ES) and Experience Level (EL) are interdependent and thet will affect the Short-Term Stress Level (SLs).

Using the wort-case scenario values mentioned above, we obtained a value of 0.829 for the Short-Term Stress Level (SLs)

| 498 | 499 | 500 |
|---|---|---|
| 0.829 | 0.829 | 0.829 |

**Fig. 5.2.** This figure shows the output of the values of Short-Term Stress Level (SLs) obtained from the workspace in the Octave, which is 0.829 at the time steps of 498, 499, and 500.

This demonstrates the model's ability to integrate various components and accurately represent their combined effects on stress levels. By confirming that the interactions between different variables produce expected results, we verify the correctness of the model's integration logic.

### 5.2 Face Validity Check

In this study, we didn't conduct a formal face validity check. Instead, we relied heavily on an extensive literature review to inform and support our pilot performance modeling and simulation. This review looked at various studies examining the effects of factors like heart rate, sleep quality, mission complexity, experience level, environmental stressors, cognitive load, physical fatigue, stress levels, reaction time, and situational awareness on pilot performance.

Our literature review brought together findings from many studies to identify key factors that influence pilot performance. Research has shown that a higher heart rate is linked to increased physical and mental stress, which can affect performance directly (Maki et al., 2022) [1]. Poor sleep quality is associated with decreased cognitive function, slower reaction times, and higher levels of fatigue, all of which can decrease the performance level. Complex missions increase cognitive load and stress, making it harder for pilots to perform well. Pilots with more experience tend to handle stress better and perform at higher levels under challenging conditions. Additionally, adverse weather and other environmental stressors can increase cognitive load and stress, leading to reduced situational awareness and performance.

There are some notable similarities between the literature and our study. The key factors identified in the literature as important for pilot performance are the same ones we used in our model. Both the literature and our model focus on the significance of cognitive load, stress levels, physical fatigue, and situational awareness. However, there are also some differences. While the literature often focuses on observational and empirical data, our study involves creating a mathematical and simulation model to predict pilot performance under different conditions. Our study combines these factors into a model that can simulate various scenarios and provide useful insights for training and mission planning.

Even though we didn't do a formal face validity check, our thorough literature review ensured that the factors and relationships included in our pilot performance model are well-supported by existing research. This approach indirectly validated our model and made it more credible by grounding it in established findings. The insights from the literature review were crucial in shaping our model and making sure it applies to real-world conditions faced by fighter pilots.

### 5.3 Sensitivity Analysis

Sensitivity Analysis plays a vital role in validating a model by evaluating how changes in input parameters affect its predictions.

First, sensitivity analysis can identify the influential variables in the model. For example, in the model, sleep quality can influence various outputs such as Physical

Fatigue (PF), Reaction Time (RT), Cognitive Load (CL), Situational Awareness (SA), and Short-Term Stress Level (SLs). By systematically varying the sleep quality parameter from 0 to 1, the sensitivity analysis reveals how changes in sleep quality affect these outputs.

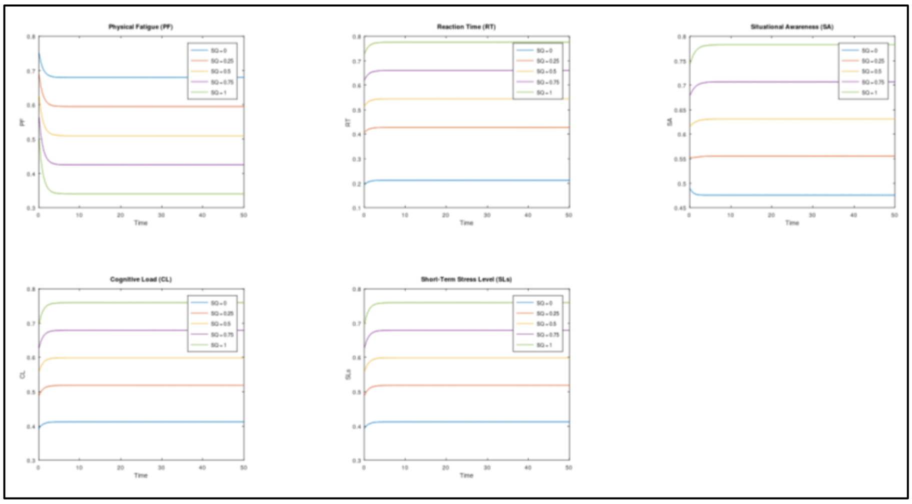


**Fig. 5.3.** This figure shows the impact of different sleep quality (SQ) on several inputs: physical (PF), Reaction Time (RT), Situational awareness (SA), Cognitive Load (CL), and Short-Term Stress Level (SLs) over time.

As sleep quality improves from 0 to 1, we can notice that there is a decrease in physical fatigue, indicating that better sleep quality results in lower levels of fatigue. Conversely, reaction time becomes faster, and situational awareness enhances with higher sleep quality, highlighting the cognitive benefits of adequate rest. However, the cognitive load and the short-term stress levels increase over time possibly because they are not significantly impacted by sleep quality but influenced by other factors.

This sensitivity analysis emphasizes the critical role of sleep quality in influencing various physiological functions, declaring that optimal sleep is essential for maintaining high performance and well-being.

## 5.4 Local Sensitivity Analysis

The local sensitivity analysis of pilot performance is evaluated by using three key factors: Sleep Quality (SQ), Mission Complexity (MC), and Experience Level (EL).

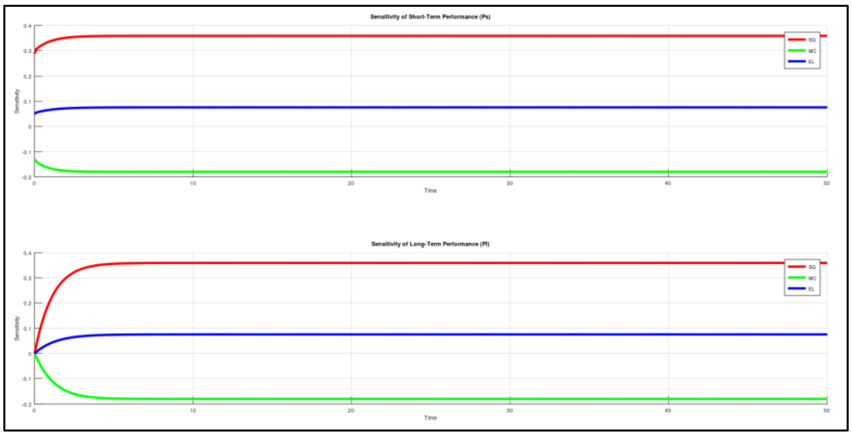


**Fig. 5.4.** The figure shows how each of the factors influences Short-Term Performance (Ps) and Long-Term Performance (Pl).

### Sleep Quality (SQ)

Sleep quality plays a crucial role in both short-term (Ps) and long-term (Pl) pilot performance. The sensitivity analysis demonstrates that good sleep significantly boosts performance, with the positive effect becoming evident almost immediately and remaining strong over time. By perturbing the sleep quality parameter by a small amount and observing how Ps and Pl respond, the sensitivity plots reveal that an increase in sleep quality leads to a notable improvement in performance. The sensitivity values for both Ps and Pl start at around 0.3 and rise to stabilize at about 0.4, underscoring the importance of rest. Consistent high-quality sleep is essential for pilots to maintain their focus, alertness, and overall effectiveness during their missions.

### Mission Complexity (MC)

Mission complexity initially creates a significant challenge for pilots, negatively impacting their performance. When mission complexity increases, the sensitivity analysis shows a starting value of around -0.2, indicating that more complex missions initially lower performance. However, as time passes, these negative values move closer to zero, showing that pilots gradually adapt to the increased complexity. This suggests that pilots can overcome the initial difficulties posed by complex missions, demonstrating their adaptability and resilience. Even though pilots eventually adjust, the effort required to manage complex missions is always greater compared to other factors. This constant demand for adaptation makes mission complexity a consistently challenging aspect of pilot performance.

**Experience Level (EL)**

Experience level positively influences pilot performance, though to a lesser extent than sleep quality. Sensitivity analysis shows that an increase in experience level leads to a modest improvement in both short-term and long-term performance metrics (Ps and Pl). The sensitivity values for experience level (EL) are smaller than those for sleep quality (SQ) but remain stable over time. This indicates that while experience enhances performance consistently, it does so in a more gradual manner compared to sleep quality. This underscores the importance of accumulated knowledge and practice in enhancing decision-making and efficiency.

In summary, sleep quality, mission complexity, and experience level significantly influence pilot performance. Sleep quality has the most significant positive impact, enhancing both short-term and long-term performance almost immediately and maintaining its influence over time. On the other hand, mission complexity initially affects performance negatively but improves gradually as pilots adapt to it. Experience level provides a smaller positive contribution to performance, emphasizing the importance of accumulated knowledge and practice.

## 5.5 Approach of Validation using Historical Performance Data

To validate the model using historical performance data, we first need to gather the historical performance data from past fighter pilot missions. Then, we compare the model's predictions with the historical data to evaluate its accuracy. After that, we also have to conduct a statistical analysis using statistical tests like T-test to ensure a better evaluation in order to determine if there are significant differences between the model's predictions and the historical data.

## 5.6 Validation using Human Experiment Data

To validate the model using human experiment data provided, we started by formulating the appropriate hypotheses for the null hypothesis ($H_0$) and the alternative hypothesis ($H_1$).

- Null hypothesis ($H_0$): The model's predictions are not significantly different from the data provided.

- Alternative hypothesis ($H_1$): The model's predictions are significantly different from the data provided.

To test these hypotheses, we selected an appropriate test statistic. We used a paired sample t-test since the data provided were normally distributed to compare the means of performance obtained from our model with the actual performance.

We then calculated the p-value based on the test statistic. Given a significance level ($\alpha$) of 0.05, if the p-value is less than 0.05, we reject the null hypothesis and conclude that there is a significant difference between the model's predictions and the provided data. Conversely, if the p-value is greater than 0.05, we do not reject the null hypothesis, indicating that the model's predictions are not significantly different from the actual performance.

| Performance (P) | Performance (P1) | Performance (P2) | Performance (P3) |
|---|---|---|---|
| 0.5774 | 0.71858 | 0.69892 | 0.6498 |
| 0.5705 | 0.493623315 | 0.4809 | 0.44626 |
| 0.7899 | 0.7973 | 0.77165 | 0.70471 |
| 0.2886 | 0.33207 | 0.32438 | 0.30208 |
| 0.9264 | 0.9961 | 0.94984 | 0.87893 |
| 0 | 0.1549 | 0.36232 | 0.1438 |
| 1 | 1.001 | 0.75356 | 0.88786 |
| 0.7382 | 0.67113 | 0.69964 | 0.60491 |
| 0.4368 | 0.46983 | 0.56343 | 0.42483 |
| 0.7316 | 0.69479 | 0.66349 | 0.62837 |
| | p-value=0.30855566050814 | p-value=0.692327103026288 | p-value=0.217910933750441 |

**Fig. 5.5.** This figure shows the p-values obtained from paired sample t-tests comparing the actual performance data against three different sets of calculated performance data which were generated by varying specific parameters within the model.

The p-values for these comparisons are 0.3086, 0.6923, and 0.2179, respectively. Since all p-values are greater than the significance level of 0.05, so we do not reject the null hypothesis in any of the cases. This indicates that there are no statistically significant differences between the actual performance data and any of the calculated performance data sets.

Consequently, the model's predictions are not significantly different from the observed data, suggesting that the model's performance is consistent with the actual performance. This statistical validation supports the accuracy and reliability of the model in predicting performance outcomes.

# 6 Application

By incorporating our model into training scenarios or even real-life situations, pilots can enhance their skills in a controlled environment. This allows them to practice multiple times safely before actually flying a jet. Additionally, this model aids trainers in crafting scenarios that mimic real-world challenges, enabling pilots to manage stress effectively while maintaining high performance across various mission levels.

The model allowed trainers to customize the various training scenarios for each pilot. For example, if a pilot struggles with stress at simpler tasks, the training can gradually increase in difficulty to build their adaptation towards the mission. The model provides detailed performance reports, pinpointing areas that need improvement and tracking progress over time. This assessment helps trainers adjust future sessions to address weaknesses and build on strengths. Trainers can also modify scenarios in real-time based on the pilot's physiological and performance data. As pilots get used to one level of difficulty, trainers can introduce tougher scenarios, preparing them for real-life missions in a jet.

It is useful and practicable to use wearable technologies and sensors to collect data for the model. These gadgets monitor a range of performance and physiological indicators in real time without interfering with the pilot's tasks. Heart rate, sleep habits, and other vital indicators are tracked by wearable devices such as headbands, chest straps, and smartwatches. These small, light sensors are ideal for constant observation while training and flying. More data for the model may be added by using cockpit sensors to monitor environmental stresses including temperature, noise, and uneven air movement. Wearable technology ensures real-time data availability for analysis by enabling wireless data transmission via Bluetooth or Wi-Fi to a central system. Cloud systems offer secure storage of data, facilitating simple access and scalability. Given the sensitivity of the data, maintaining privacy and security is critical. Advanced algorithms and machine learning can analyze this data to detect trends and make predictions, with processing taking place on powerful computers for fast and reliable results.

By incorporating the pilot performance model into training, pilots are better prepared for stressful situations through realistic simulations and personalized training. The effective use of wearable technologies and sensors to collect data is seamlessly integrated into training programs, improving pilot preparation and performance.


**Fig. 6.1.** This figure shows the form to let users (trainers) add new conditions by filling in the date, sleep quality, experience level, mission level, heart rate and weather. Then, the value of the percentage will be calculated and shown in the list of conditions in **Fig. 6.2**.

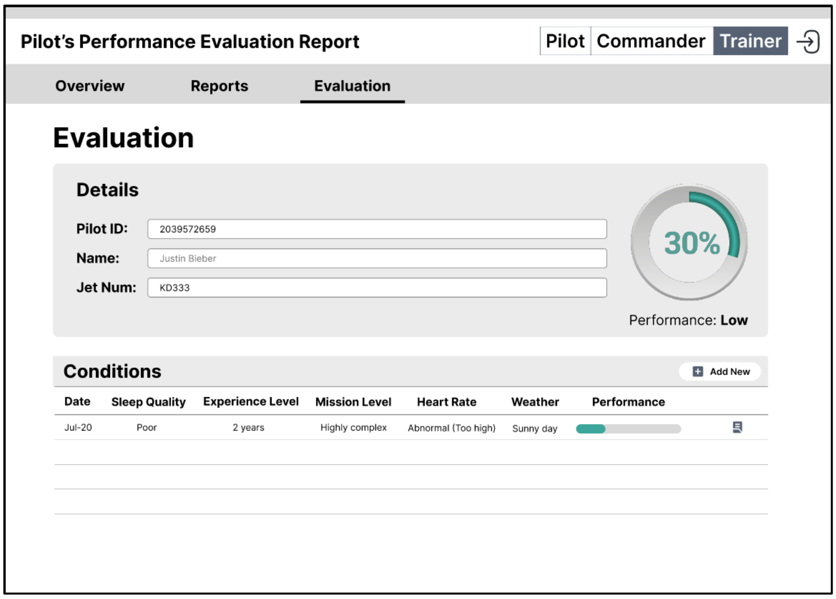


**Fig. 6.2.** This figure represents a user-friendly interface of pilot's performance evaluation report which will display the performance data, including the overall percentage of performance, the details of the conditions in the list of conditions like date, sleep quality, experience level, mission level, heart rate, weather and the performance on that day for different users like pilots, trainers, and commanders.

This interface enables different users to interact with the model's outputs effectively. Pilots can review their performance metrics and understand the impact of various conditions on their stress and performance levels. Trainers can use this data to tailor training programs and provide feedback. Commanders can monitor the overall performance of their pilots and make informed decisions based on the data provided.

# 7 Conclusion

By examining key input features such as heart rate, sleep quality, mission complexity, experience level, and environmental conditions, we sought to understand their impact on cognitive load, stress levels, physical fatigue, situational awareness and overall performance.

We developed a complex mathematical model to cover these factors by constructing detailed mathematical equations and simulating a range of scenarios through both instantaneous and temporal relationships. This model was then strictly validated using various methods, including mathematical analysis, unit testing, integration testing, sensitivity analysis, using human experiment data with statistical analysis via paired sample t-tests to ensure the model's accuracy.

From this study, we found that sleep quality had the most significant positive impact on pilot performance that will enhance both short-term and long-term performance. Mission complexity initially affected performance negatively, but pilots gradually adapted to complex missions, and they could adapt in the long-term. Experience level also positively influenced performance as knowledge and practice could be accumulated.

In conclusion, this case study provides valuable insights into the factors affecting fighter pilot performance and emphasizes validation of mathematical model in enhancing training and mission planning. The effectiveness and safety of pilot operations can be enhanced by prioritizing foundational accuracy in model development, and finally contributing to better mission tasks.

## 8 Reflective

Through this project, we learned a lot about modeling human fighter pilot performance, particularly how cognitive load, physical fatigue, reaction time, situational awareness, and other factors interact and impact pilot performance both short-term and long-term. The most challenging part was building the initial conceptual model and mathematical equations. We realized that any errors at this stage would lead to inaccuracies in all subsequent stages, including case scenarios, evaluations, and results. Looking back, we wish we had a clearer understanding of how to structure and validate our initial models and equations before diving deeper. If we were to approach this project again, we would allocate more time to ensure that our initial models and equations were correct. Our advice to future students is to focus extensively on the initial stages of conceptual modeling and ensure a strong understanding of the equations. A solid foundation will save time and effort later and lead to more accurate results.

## 9 References


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# 10 Appendix

## 1. Prototype of Interface

The prototype of the interface can be viewed using the Figma link shown below.

https://www.figma.com/design/5aHyUkvLWzRMFqdQrUfjmi/Pilot's-Performance-Evaluation-Report?node-id=0-1&t=vpEzb7j3xKjj2xDA-1