Performance Trends during Sleep Deprivation

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Abstract

Background: Understanding human behavior under the effects of sleep deprivation allows for the mitigation of risk due to reduced performance. To further this goal, this study investigated the effects of short term sleep deprivation on using a tilt-based control device and examined whether existing user models accurately predict targeting performance.

Methods: A task in which the user tilts a surface to roll a ball into a target was developed to examine motor performance. A model was built to predict human performance for this task under various levels of sleep deprivation. Ten participants completed the task every two hours until they reached 24 hours of wakefulness. Performance measurements of this task, which were based on Fitts' law, included movement time, task throughput, time intercept.

Results: The model predicted significant performance decrements over the 24-hour period with an increase in movement time (R^2 = 0.61), a decrease in throughput (R^2 = 0.57), and an increase in time intercept (R^2 = 0.60). However, it was found that in experimental trials there was no significant change in in movement time (R^2 = 0.11), throughput (R^2 = 0.15), or time intercept (R^2 = 0.27).

Discussion: The results found were unexpected as performance decrement is frequently reported during sleep deprivation. These findings suggest a reexamination of the initial thought of sleep loss leading to a decrement to general function.

Keywords: Cognitive Modeling, Fitts' Law, Motor Control, Sleep Deprivation, Vigilance

Introduction

There are a significant number of professions that frequently require working long hours or late at night that can lead to remaining awake for extended periods of time, causing sleep deprivation. It is important to understand the exact effects that sleep deprivation can cause so that it may be possible to anticipate a person's performance after a long shift, ameliorate decrements, and potentially prevent life threatening errors. Performance can manifest in many different forms; one way to examine it is in field of human-computer interaction (HCI). HCI is the primary mode from which humans perform crucial tasks in any environment, regardless if it is on the ground, underwater, or up in the air.

In general, most computer input is done with three major tools: keyboard, touch screen, and mouse. However, interface interactions have expanded with mobile technologies and the wide spread use of gyro sensors and accelerometers, which have added a new dimension for HCI in the form of tilt-based control. The implications of tilt as an input method are far reaching. Tilting goes well beyond the other control systems in that it allows for a complex input parameter in a 3-dimensional space, which can be particularly useful for above ground operations. Tilt devices can also be used in situations when the use of a computerized system is extremely advantageous, but there are physical limitations associated with the task that constrain the use of other devices. With the advancement of tilt based interaction, it is becoming more important to characterize and quantify a person's performance and accuracy using such an interface.

There are methods that start to model such behavior, such as cognitive architectures. One frequently used architecture that can be used to model HCI tasks is EPIC.[12] While models developed in this architecture provide significant insight, the accuracy of these can be improved because they are still missing many components, for example those related to sleep deprivation.[9] In addition, even the proposed mathematical models used to alleviate these drawbacks are very general, and may not encompass the necessary depth for reasonable insight. Thus, this study examines how wakefulness or acute sleep deprivation affects the performance of people using tilt-based devices through modeling as well experimentation to evaluate the predictive power of the models.

In general it has been established that sleep deprivation has the most significant effect on alertness and attention, frequently causing lapses or short periods of non-action following a stimulus.[1,16,24] These types of lapses are particularly seen in psychomotor vigilance tasks, in which a person waits for a stimulus to respond. In addition, it has been shown that sleep deprivation can result in an overall slowing of responses in general.[15] However, the slowing of cognitive processing has also been observed, independent of lapses.[1] Beyond that, sleep deprivation also increases the rate at which people make errors of omission and commission, many of which are partly caused by failures in vigilant attention.[1]

With the varied results in literature regarding sleep deprivation there are three general views on the effects of sleep deprivation. The first is based on controlled attention and suggests that tasks which are cognitively highly demanding are unaffected by short sleep deprivation.[15] It is also found that tasks that are more monotonous or less engaging are more affected by sleep deprivation as described by the controlled attention model.[23] Finally, a neuropsychological based hypothesis describes sleep deprivation as causing lower activation in the prefrontal cortex region of the brain.[4,15] This suggests that tasks that are oriented toward the pre-frontal cortex are more susceptible to sleep deprivation.[7] Even with these hypotheses, many argue that sleep loss exerts a non-specific effect on performance, and most modeling efforts have been based of this idea.[3,10,15,20]

This study focuses on examining human movement with the control of interfaces for the goal of finding metrics that can describe, and consequently characterize, a person's performance on additional measures. To do this we utilize Fitts' Law, which, describes a psychological model of human performance, and has been used to provide information regarding how the human psychomotor system processes targeting tasks.[8,11,14,18,21,25]

To increase the understanding of the relationship between sleep deprivation and human performance, some groups have chosen to simulate sleep deprivation tasks using computational cognitive modeling within a cognitive architecture.[9] Unlike many standard mathematical modeling techniques, cognitive architectures act as a blueprint for cognition and focus on predicting human behavior during specific tasks.[6] The architecture incorporates various basic information processing mechanisms predictably used by humans collected in literature (e.g., memory retrieval, typing speed, saccadic velocity), and allows a computer to simulate tasks based on human abilities.[12]

One of the drawbacks of computation architectures is the lack of accurate ways for predicting the changes in the processing mechanisms of cognitive models due to sleep deprivation.[9] Gunzelmann et al.[9] have made an attempt at characterizing the effects of sleep deprivation within the Adaptive Control of Thought—Rational (ACT-R) cognitive architecture. The architecture adaptations consisted mainly of the manipulation of constants that influenced the information processing systems of the architecture based on the time an individual had spent continuously awake. The manipulation performed leads to a steady increase in errors of commission, median reaction time, and number of lapses as the simulated time awake increased during tasks.

While this work was informative, cognitive architectures are constantly evolving and some of the variables used in the previous study are no longer part of the newer cognitive models as they are updated and changed.[5] Some of the variables no longer in use include quantitative “goal values” that influence the model’s choice in action, as well as preprogrammed probabilities of success for individual actions.[9] Thus, there is a need to gain more information on how conditions, such as sleep deprivation, affect human performance to better incorporate the information into newer models. For this study, the current models in the architectures are used as a precursor to predict results so that they may be compared to the empirical data, and it can be determined if there are portions of the cognitive architecture that should be replaced in the future.

Methods

Participants

The experiment was conducted with the assistance of 10 student volunteers from Worcester Polytechnic Institute. This research complied with the American Psychological Association Code of Ethics and was approved by the Institutional Review Board at Worcester Polytechnic Institute. Informed consent was obtained from each participant. The population consisted of 5 male and 5 female participants between the ages of 22 and 32, none of whom had any extensive experience working with gyroscopic-based devices in a manner that utilized tilt type control. Participants reported an average of 7.7 hours (SD = 0.72) of sleep each night for 7 nights prior the start of the experiment. Participants were compensated for their time.

Equipment

The experiment was performed using a Samsung Galaxy Tab 10.1 running Google's 4.1 (Jellybean) operating system. The task was done on a screen that was 14.23 cm by 21.35 cm (800 px by 1200 px) using a ball that was 0.36 cm (25 px). The software was developed in Java using the Android SDK, and tilt control was implemented using the device's built in gyro sensor. Pitch and roll values were converted to tilt magnitude and direction. The task implemented in the software allowed a user to tilt the device to control a circle that that was shown on screen. The goal of each individual task trial was to move a ball (represented by a small circle) to a target (represented by a large circle) location on the screen. The application was set up to run multiple trials, in which a single trial consisted of a particiant moving a circle on the screen of the device to the target by tilting it.

The movement of the target was controlled by the pitch and roll values produced by the user when tilting the device. In addition, the movement of the ball was influenced by a gain parameter, which was determined empirically prior to the experiment to allow for adequate object manipulation and to control the speed of trials. The velocity of the ball along with the angle of movement was calculated using equations 1 and 2, with pitch and roll in degrees from horizontal.

$$\text{Ball Velocity} = \text{gain} * \sqrt{\text{roll}^2 + \text{pitch}^2} \tag{1}$$

$$\text{Movement Angle (from horizonal)} = \arctan\left(\frac{\text{roll}}{\text{pitch}}\right) \tag{2}$$

The total number of trials in a set included 8 target positions, 1 movement gain, 1 ball size, 3 target sizes, 2, target distances, and 5 repetitions for a total of 240 trials per set. Table 1 shows the independent variables used. The combinations of these variables were presented in a random order for all trials to eliminate sequence effects.

Table I

Independent variables and task values

Independent Variables	Values
Target Position (° from horizontal)	0, 45, 90, 135, 180, 225, 270, 315
Movement Amplitude (cm (px))	2.22 (125), 4.45 (250)
Target Size (cm (px))	0.71 (40), 1.07(60) , 1.79 (100)
Time Awake (hours)	6, 8, 10, 12, 14, 16, 18, 20, 22, 24

Procedure

Creating a model prior to the experiment allowed for parallel analysis of the results. The purpose for choosing to create a model rather than just use a function that defines performance through sleep, is to ensure that the modeling effort incorporates as many factors of cognition available to account for factors outside a simple task performance relationship. The EPIC architecture was chosen for this study due to its capacity to model gyroscopic tasks.[19] The task environment and production rules were prepared within the cognitive architecture. The control of the simulation was based on Fitts' law movement, as it has been shown that gyroscopic control tasks on a mobile device adhere to Fitts' model, shown in equation 3.[19]

$$\text{Movement Time} = a + b * \text{ID} \tag{3}$$

In Fitts' law the a variable is the time intercept, or the minimum amount of time required for completing a task. The b variable is the slope, or the increase in movement time, as the difficulty of a task increases. The inverse of the slope is the index of performance (IP), also referred to as throughput, which, represents a quantitative value for the ability to perform with increasing difficulty. Thus, task completion time was based on the parameters of time intercept and index of performance as well as the properties of the task.

The model was designed with the parameters and independent variables, to precede in the same manner as the experiment. The production rules had the model search for the target and then move the ball to the center. The values of time intercept and IP were changed over time, based on the performance effective changes described in the Sleep, Activity, Fatigue, and Task Effectiveness (SAFTE) model (mathematical model describing task effectiveness with sleep deprivation) to simulate wakefulness between 6 and 24 hours awake.[9,10] The equation describing SAFTE is shown in equation 4.

$$\mathrm{E}(t) = 100 * \frac{R(t)}{\mathrm{R_c}} + \mathrm{C}(t) + \mathrm{I} \tag{4}$$

The SAFTE equation describes task effectiveness as E(t) based on three parts. The $100*R(t)/R_c$ term representing the reservoir level or homeostatic sleep drive describing change in effectiveness with fatigue.[10] C(t) represents the circadian process function or rather the change in task effectiveness alongside the circadian rhythm.[10] Finally, *I* describes sleep inertia or the time of lesser task performance shortly after waking.[10] The equation was implemented within the EPIC model using the parameters described by Hursh et al.[10] and used to modify various performance variables within the EPIC architecture's manual aimed movement module. A diagram describing how the variables were changed and derived is shown in Figure 1.[10]

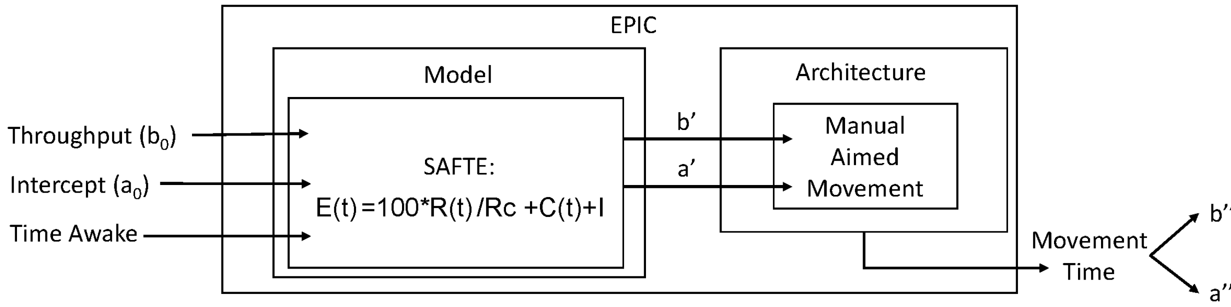

Figure 1. Illustration of the manipulation of performance variables and implementation of SAFTE within EPIC. The variables of b_0, b', and b'' represent the input performance parameter, the varied performance parameter, and the derived one respectively. The variables of a_0, a', and a'' represent the input intercept parameter, the varied intercept parameter, and the derived one respectively.

The IP (b), used in movement calculations, was changed by decreasing the mean value based on time awake and the on effectiveness in the SAFTE model. The time intercept (a) parameters was also changed by increasing it based on the number of hours awake and effectiveness. These changes were designed in an effort to simulate lapses, and were meant to integrate with the EPIC library established by Kieras et al.[13]. This model was run to simulate 10 people, each doing 240 actions or trials per 2 hour period, totaling to 2400 runs for every simulated period of wakefulness or 24,000 total runs.

For the experimental portion, participants were asked to refrain from consuming any stimulants and depressants for 48 hours prior to the start of the experiment, and were advised to keep a normal and consistent sleep schedule for 1 week prior to the study. All particiantss submitted journals containing their sleeping and eating habits for the week before the experiment, which indicated compliance.

Each particiant completed a set of 240 movements over a 20 to 30 minute session, a session occurred every two hours over a period of 24 hours. Throughout all experimental periods, an experimenter monitored participants to ensure that they remained awake. The time at which participants awoke during the day of the trial was monitored, and participants began the experiment four hours after waking up. The first two sessions were considered learning sessions and not were not included in final data analysis. All subsequent trials were run every two hours until the point at which the participant had remained awake for 24 hours.

Once the experiment began, a start screen was provided between each task. A trial began once a button that appeared on the screen and was pressed by the participant. At this point a target appeared on the screen and the ball in the center moved as the device was tilted. A target was considered acquired or successfully hit once the circle remained within the target area for a total of 500 ms.

Analysis

To use Fitts' law to measure the performance, we determine the difficulty of every task. The task difficulty, referred to as index of difficulty (ID), is shown in equation 5, and is derived based on the movement distance required to move to a target and the width of that target. The width used is the effective width of the task (the difference in size between the target and the ball) rather than the width of the target itself, as the effective width estimates the target width focused on by the participant, and has been determined to be more accurate for the purposes of determining difficulty of a task.[17,19] The other performance parameters of throughput and time intercept are calculated based on the formula for Fitts' law, shown in equation 3.

$$\text{Index of Difficulty} = \text{Log}_2\left(1+\frac{\text{Distance}}{\text{Width}}\right) \qquad (5)$$

Because this task continues until a target is reached, we examine additional measures of accuracy which are movement variability, movement error, and number of target exits and reentries. These metrics are based on the path that the participants take to reach the target and the ideal most direct path. From this point, we will refer to the distance between any point on the actual path and the ideal path as y_i. In addition, there is the average path taken by a person, and we will refer to the distance between the average path and the ideal path as $\overline{y}$.

The first measure of accuracy, movement variability, examines the extent to which the movement path, taken by a participant, lies along a mean line parallel to that of the original task axis. The calculations for movement variability is the same that was used by MacKenzie et al.[19] for the evaluation of accuracy measurement (equation 6).

$$MV = \sqrt{\frac{\sum (y_i - \bar{y})^2}{n-1}} \tag{6}$$

Movement error compares the movement of the participant's path directly to the ideal task axis. Once again, the calculation for movement error was done using the same calculation as Mackenzie et al.[19] and is shown in equation 7. Finally, target exits and reentries describes the number of times that a participant exited and entered the target before successfully remaining inside for 500ms.

$$ME = \frac{\sum (y_i)}{n} \tag{7}$$

Results

The variables examined with the model were minimum task time, index of performance, and a noise gain value added to the Fitts' equation, as those values represented the ability of a person to perform a task. The results are shown in Figure 2. Though second order affects appear to be present, linear regression is used to test for general trends. It was found that average predicted movement time increased over time $R^2 = 0.61$, $p < 0.01$. The average predicted throughput decreased over time, $R^2 = 0.57$, $p < 0.01$. The average intercept increased over time, $R^2 = 0.60$, $p < 0.01$.

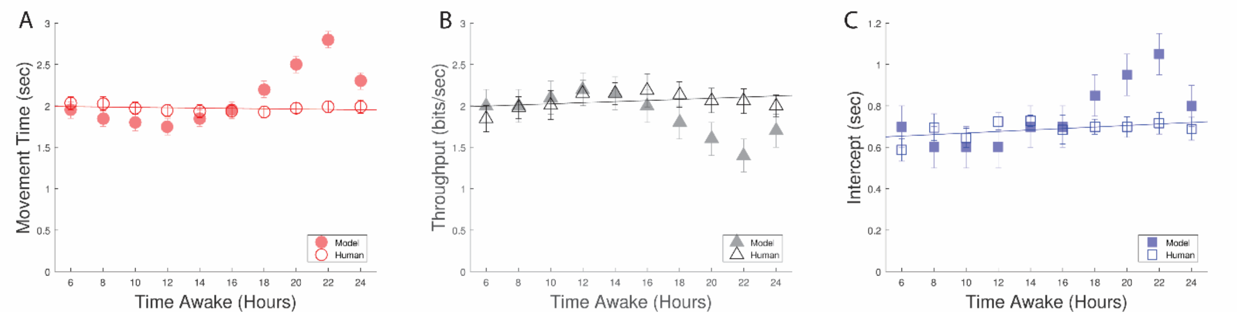

Figure 2. (A) The average movement time (±SEM) across all participant data (open markers) and the model predication (solid markers). (B) The average throughput (±SEM) across all participant data (open markers) and the model predication (solid markers). (C) The average intercept (±SEM) across all participant data (open markers) and the model predication (solid markers).

The performance data can also be visualized in the average performance lines for each time awake and difficulty curves in Figures 3A and 3B, which display how movement times change with the difficulty of the task. It is possible to see a general increase in movement time with hours awake along with an influence of circadian rhythm especially after 24 hours in the model results. The performance lines and difficulty curves once again show the significant change in performance across various measures as time awake increases.

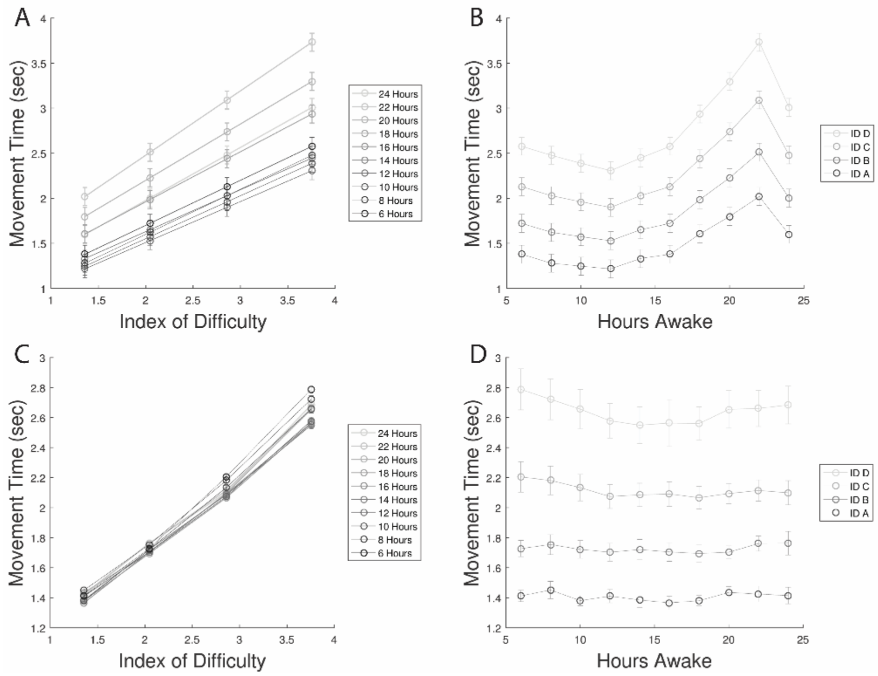

Figure 3. (A) Average predicted performance lines representing movement times for the levels of IDs and sleep deprivation (±SEM). (B) Predicted difficulty curves for each ID showing movement times for 4 IDs, with ID values A through D representing increasing task difficulty (±SEM). (C) Average performance lines representing movement times for various levels of sleep deprivation from participant data (±SEM). (D) Difficulty curves for each ID showing movement times for 4 IDs, with IDs A through D representing increasing task difficulty from participant data (±SEM).

The performance lines, based on the output of EPIC, show a culmination of the three metrics: movement time, throughput, and intercept. Unfortunately, the EPIC architecture does not have a way of simulating accuracy, and therefore only these predictions can be used.

Following creation of the model, ten participants performed all the movement tasks without data loss or having to restart. The R^2 between the index of difficulty and average movement time was computed for every set of 240 trials. Over 100 sets of trials (10 participants over 10 sessions), the average

R^2 value was .99 with a standard deviation of 0.015. This provides strong evidence that movements in the tasks examined in this study were in fact Fitts' movements.

Data from the learning trials showed that performance followed the power law of learning and did not appear to be significantly affected by fatigue, and showed a plateau by the end of the second session for each person.[22] Figure 2 show the average movement time, throughput, and intercept values from each participant that were taken for each set of trials, overlaid on the predictions from the model. These values were then averaged and compared to hours awake. After examining overall trend using regression and performing one-way ANOVA analysis in conjunction with Dunn-Sidak post-hoc to look for differences in performance between different levels of wakefulness, it was found that over the period of 24 hours, there was no reliable change in movement time $F(9,90) = 0.26$, , $R^2 = 0.11$, $p = 0.35$. In addition, no reliable change in throughput was found $F(9,90) = 0.45$, $R^2 = 0.15$, $p = 0.26$. Finally no change was found with intercept $F(9,90) = 0.69$, $R^2 = 0.27$, $p = 0.12$. All results show no significant change in performance as time awake increases.

Average performance lines and difficulty curves, based on equation 5, and are shown in Figures 3C and 3D. The performance lines and difficulty curves once again show that the movement time, throughput, and intercept have no reliable changes as participants become more susceptible to sleep deprivation.

Accuracy based measurements were also taken in the form of movement variability, movement error, and movement reentries. Similar to the performance results, after regression and performing ANOVA analysis with Dunn-Sidak post-hoc analysis, it was found that was no noticeable change in movement variability with time awake $F(9,90) = 0.15$, $R^2 = 0.15$, $p = 0.03$. There was also no noticeable change in movement error $F(9,90) = 0.35$, $R^2 = 0.35$, $p = 0.01$, and no noticeable change in movement reentries $F(9,90) = 0.35$, $R^2 = 0.32$, $p = 0.01$. Figure 4 shows the data for all accuracy based measurements for all participants and difficulties, there are not corresponding predictions from the model.

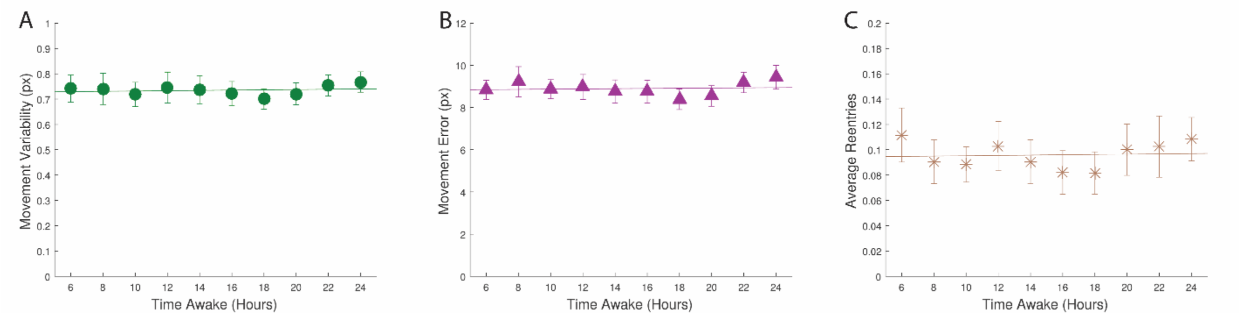

Figure 4. (A) The average movement variability (±SEM) for all participant data. (B) The average movement variability (±SEM) for all participant data. (C) The average reentries (±SEM) for all participant data.

Discussion

The purpose of this study was to determine how the performance of a person performing a tilt-based interface task changed over the course of 24 hours awake, and how that performance compared to existing models (i.e., SAFTE). When modeled within the EPIC architecture, the model predicted a decrement in performance with increased time awake in the three performance measures of movement time, throughput, and intercept. However, the predicted changes were not supported in the experiment. Like other models, the parameters were modified on the number of hours awake alone. The relationship between hours awake and how the individual parameters vary is more complex than what was modeled and seems to be also dependent on the task at hand. This implies that the predictions for the task demonstrated in this study were not as expected based on current models of sleep loss.

Because the model's predictions do not correlate with the experimental measurements, it was useful to examine the results of the observational data, starting with the average movement time to complete a task. This measurement represented the full action as a whole, and allows for simple evaluation of the performance of the participants. The final results provided evidence that the average movement time did not change over the period of sleep deprivation, which is consistent with previous sleep deprivation tasks that employed a psychomotor vigilance task nor with the model's predictions.

Previous studies have found that reaction time for psychomotor vigilance tasks, tasks that frequently cause lapses in participants, increased clearly and distinctly with wakefulness.[15]

Examining the difference between this task and others it is reasonable to examine aspects of this experiment and task that may have caused these differences. It is unlikely that learning effects had a significant influence on the results, as any effects would have been detected in early trials and would need to identically keep pace with fatigue throughout the entire experiment. The sample size could also be increased; however, the low standard error empirically suggests that increasing the sample size to the point of finding significance will lead to low ecological relevance.

The examination of the index of performance in this study represents the throughput of information being processed by the participants. This measurement represents the increase in time necessary to complete a task as the difficulty increases. It was found that over a period of 24 hours of sleep deprivation that the throughput of participants did not significantly change between trials, meaning that there was no increase in time between tasks of different difficulties as the participants became more sleep deprived. While this particular experiment did not show any change in throughput, it is possible that a difference in performance could be found if certain parameters of the experiment were altered such as the hours awake, velocity gain, or the range of index of difficulties.

The intercept, representing the minimum time required to complete a task, also did not significantly change with increasing sleep deprivation. This value is affected by many of the same parameters that affect throughput. However, unlike throughput, the intercept could also have been affected by the start screen interface, which removed some of the psychomotor vigilance elements of this task. A button between each trial was meant to create consistency between trials as well as provide definitive start and stop times for each task that were controlled by the participant. However, because the start time was defined by the participants, one element where lapses could occur was removed. A different type of interface or pause between trials could show an increase in intercept with increasing hours awake, however, it would change the type of task (i.e., make it a vigilance-based task).

The accuracy of the tasks was also found to not have a significant change over a wakeful period of 24 hours. This indicated that the motor skills of the participants did not appear to decrease over time, and were able to retain their accuracy while simultaneously retaining their performance over the period of wakefulness. There does appear to be influences on task completion time from circadian rhythms, but they were muted in this task. Thus, there is not a speed-accuracy trade off masking effects of sleep loss on response time.

Taking into account that all performance and accuracy measurements remained consistent over the 24 hour period, the previous assumption that performance and accuracy would decrease with increased wakefulness did not hold true, as was expected from previous research regarding psychomotor vigilance and wakefulness and included in our model from the SAFTE model.[10,23] It was found that for this type of task, the previous general decrement with sleep loss does not accurately predict an individual's activity for this task.

In this particular experiment, the type of task presented to the participants was a more active task and it was possible that it did not require the level of vigilance to complete as other similar tasks, which could explain why there was no effects of sleep loss. This was unexpected because this task seemed to require low levels of engagement and was fairly monotonous and thus based on the controlled attention hypothesis it would be susceptible to sleep deprivation.[23] Thus, one possibility for a lack of change in performance be that the task was simply more engaging than those tasks used in the past. However, this task did not have nearly the wide range of information processing as those task explored when examining control attention, and a high degree of engagement for this task could be of a different type. [23]

Another potential alternative for the performance observed in this study could be that the task in this experiment used different or additional cognitive or perceptual motor processes than initially thought. For example, if this this task caused lower activation in the prefrontal cortex, but higher activation elsewhere, the prediction based on the neuropsychological hypothesis would not hold.[4] The tilt-based task was also only run for a period of 20 minutes every 2 hours, which may not have been long enough to induce potential time-on-task effects or the induction of conceivable intertwining between sleep deprivation and time-on-task.[2] Finally, while this study examined participants that were kept awake for 24 hours, it may be that people did not reach the level of sleep deprivation needed to be affected.

In addition to the lack of consistency with psychomotor tasks, when working with psychological modeling, there are significantly more processes that need to be taken into account than just how long an individual has been awake. In the prediction model developed by Gunzelmann et al.[9], variables that controlled throughput, accuracy, and error were varied based entirely on an individual's wakefulness. Other mathematical models that estimate performance based on sleep deprivation use a blanket variable of percent performance to all tasks in a non-specific manner.[10,20] However, it is very likely that the relationship between task specific cognitive processes and fatigue dependent cognitive processes needs to be clearly defined before a more accurate model for prediction can be built.

This study modeled and empirically examined the change in users' performance and accuracy while using a tilt-based control device over a period of 24 hours of sleep deprivation. The model, based on information in the literature predicted that there would be a significant change in performance. The observed performance parameters of movement time, throughput, and average intercept did not significantly change over the duration of the experiment, which differed from the expected prediction of the model. In addition, the accuracy parameters of movement error, movement variability, and number of reentries also did not change over the experimental period. The sustained performance and accuracy over this time period for this type of control does not follow previously found parameters from psychomotor vigilance tasks. The results suggest that this task was not affected by sleep deprivation within the time period tested. The findings presented here undermine the notion that fatigue affects all performance tasks equally as is currently predicted.

In the future, the next steps would be to examine varied psychomotor tasks such as the one examined in this paper to determine which aspects are more or less affected by sleep deprivation. This information can lead to valuable data that can be used to improve theories of the effects of sleep loss as they are realized in cognitive architectures.

A few changes could be made to this type of experiment that would allow a deeper examination of tilt-based control. The first would be in using a wider range of task difficulty (e.g., smaller targets) to see if differences can be found at higher levels of difficulty. Next, the interface between trials could be changed to mimic a participant receiving a specific stimulus so that more possibilities for lapses to occur could be introduced.

Finally, while decrements are seen in other tasks within 24 hours, that sleep loss time span may not have been a long enough time to see performance degradation from sleep deprivation on this task, and future studies may look to increase this time, as studies have shown that time awake is one of the most significant factors when examining between-studies variability.[15] However, these results suggest that perceptual-motor skills may be more robust against sleep fatigue than other components of thought.

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Tables

Table I

Independent variables and task values

Independent Variables	Values
Target Position (° from horizontal)	0, 45, 90, 135, 180, 225, 270, 315
Movement Amplitude (cm (px))	2.22 (125), 4.45 (250)
Target Size (cm (px))	0.71 (40), 1.07(60) , 1.79 (100)
Time Awake (hours)	6, 8, 10, 12, 14, 16, 18, 20, 22, 24

Figure Captions

Figure 1. Illustration of the manipulation of performance variables and implementation of SAFTE within EPIC. The variables of b_0, b', and b'' represent the input performance parameter, the varied performance parameter, and the derived one respectively. The variables of a_0, a', and a'' represent the input intercept parameter, the varied intercept parameter, and the derived one respectively.

Figure 2. (A) The average movement time (±SEM) across all participant data (open markers) and the model predication (solid markers). (B) The average throughput (±SEM) across all participant data (open markers) and the model predication (solid markers). (C) The average intercept (±SEM) across all participant data (open markers) and the model predication (solid markers).

Figure 3. (A) Average predicted performance lines representing movement times for the levels of IDs and sleep deprivation (±SEM). (B) Predicted difficulty curves for each ID showing movement times for 4 IDs, with ID values A through D representing increasing task difficulty (±SEM). (C) Average performance lines representing movement times for various levels of sleep deprivation from participant data (±SEM). (D) Difficulty curves for each ID showing movement times for 4 IDs, with IDs A through D representing increasing task difficulty from participant data (±SEM).

Figure 4. (A) The average movement variability (±SEM) for all participant data. (B) The average movement variability (±SEM) for all participant data. (C) The average reentries (±SEM) for all participant data.