Lecture Notes in Networks and Systems 264

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Advances in Simulation and Digital Human Modeling

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Editors

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Advances in Human Factors and Ergonomics 2021

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12th International Conference on Applied Human Factors and Ergonomics and the Affiliated Conferences (AHFE 2021)

Proceedings of the AHFE 2021 Virtual Conferences on Human Factors and Simulation, and Digital Human Modeling and Applied Optimization, July 25–29, 2021, USA.

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Preface

This volume is a compilation of cutting-edge research regarding how simulation and modeling supports human factors. The compilation of chapters is the result of efforts by the International Conference on Applied Human Factors and Ergonomics (AHFE), which provides the organization for several affiliated conferences. Specifically, the chapters herein represent the International Conference on Human Factors and Simulation and the International Conference on Digital Human Modeling and Applied Optimization.

Simulation is a technology that supports an approximation of real-world scenes and scenarios for a user. For example, a cockpit simulator represents the configuration of the inside of a cockpit and presents a sensory and motor experience to mimic flight. Simulations advance research by providing similar experiences to those scenarios that would otherwise be impractical to carry out in the real world for such reasons as monetary cost or safety concerns. Simulations can support numerous goals including training or practice on established skills.

Modeling is a somewhat different tool than simulation, though the two are often used interchangeably as they both imply estimation of real-world scenes or scenarios that bypass practical concerns. The difference in the context of this book is that modeling is not intended to provide a user with an experience, but rather to represent anything pertinent about the real world in computational algorithms, possibly including people and their psychological processing. Modeling may answer questions about large-scale scenarios that would be difficult to address otherwise, such as the effects of economic interventions or smaller-scale scenarios such as the cognitive processing required to perform a task that is otherwise undetectable by measurement devices.

The goal of the research herein is to bring awareness and attention to advances that human factors specialists may make in their field to address the design of programs of research, systems, policies and devices. This book provides a plethora of avenues for human factors research that may be helped by simulation and modeling.

The book is divided into the following nine sections:

Human Factors in Simulation

1. Modeling and Simulation for Human-Human and Human-Agent Teaming
2. Visualizing Team Trust and Cohesion
3. Computational Modeling Approaches in Politics and Economics
4. Virtual and Augmented Reality
5. Simulation and Human Factors for Nuclear Control Rooms
6. Data Essential for Human Factors Simulation Modeling
7. Human Sensing in Simulation

Digital Human Modeling

8. Digital Human Modeling and Applied Optimization
9. Digital Human Modeling by Women in Human Factors

Sections 1–7 cover topics in simulation and modeling while Sections 8–9 cover topics in Digital Human Modeling and Applied Optimization.

All papers in this book were either reviewed or contributed by the members of editorial board. For this, we would like to recognize the board members listed below:

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This book covers diverse topics in simulation and modeling. I hope this book is informative and helpful for the researchers and practitioners in developing better products, services and systems.

July 2021

Julia Wright
Daniel Barber
Sofia Scataglini
Sudhakar Rajulu

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Modeling and Simulation for Human-Human and Human-Agent Teaming

Human-Autonomy Teaming with Learning Capable Agents: Performance and Workload Outcomes

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Abstract. Each of twenty participants teamed with a learning capable agent to conduct a threat classification task. The agent's reasoning and learning transparency varied across four scenarios. Access to agent reasoning transparency improved task performance as assessed by percent of correct classifications. Agent learning transparency of inferred knowledge improved task response time and reduced cognitive workload. However, when the human was burdened with directly teaching the agent, task completion time and perceived workload increased dramatically, while satisfaction in task performance decreased. These findings indicate that when teamed with learning capable agents, human performance and workload are best supported when the autonomy can derive its needed information with minimal human input.

Keywords: Human factors · Human-autonomy teaming · AI/ML · Human-robot interaction · Workload

1 Introduction

Soldiers collaborating with intelligent machine agents (e.g., robots, algorithmic planners) to conduct multiple tasks is quickly becoming a reality. Advances in artificial intelligence (AI) and machine learning (ML) continue to increase not only the abilities of these agents to conduct tasks autonomously, but also to conduct tasks of ever-increasing complexity and difficulty [1]. Learning capable agents (LCAs) are able to adapt to new information, updating their goals and reasoning without the knowledge of their human counterpart. The LCAs are not static; they dynamically learn from increasing amounts of data and experience. Thus, when human-agent teams (HATs) include LCAs, within-team communications become crucial to shared awareness and team effectiveness. The goal of this study is to examine how these advances in AI/ML task complexity and learning will affect the human teammate, specifically, how transparency of agent reasoning and agent learning affects human-agent team performance.

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2 Background

2.1 AI/ML

Advances in AI/ML have given rise to LCAs, agents that will adapt their behavior over time as their models of the world are updated by events encountered or additional data with which to update their algorithms. While the effects of agent transparency on operator performance have been studied with agents that are incapable of independently updating their goals and/or reasoning, little is known about outcomes related to human-agent teaming with a LCA; particularly how transparency of a LCA's reasoning and learning will affect the human operator.

Learning capable agents use their experiences and data to update the preprogrammed models that direct their actions and goals. One example of LCAs, image recognition agents, use camera images to understand their surroundings and inform their actions. These agents are trained for real-world tasks via presentation of a series of images prior to deployment (offline learning). During training, images are labelled and categorized, either *a priori* by the agent or post hoc with human assistance. However, it is not possible to generate labelled images of all potential threats and situations *a priori*, hence, the need for the agent to be able to continue learning after deployment [2].

There are several potential solutions for effective continual training for autonomous systems. One is that learning could occur after deployment by having the agent review the targets that the agent missed but the human identified, essentially repeating offline learning focusing on mistakes made in the real world. Another is real-time learning, where the agent infers meaning from human input and updates its programming, may create mis-interpretations initially that would reduce as more information is processed. Alternatively, on-the-job training, wherein the human teaches the agent, could be used to improve an agent's learning and performance while the team is conducting tasks in the field. There is utility to the agent being able to learn real-time after deployment, as this has the potential to create a more agile, responsive battle force in addition to reducing the time required for additional offline learning. In this study, the simulated agent will use information supplied by the human during missions to update its knowledge base offline (i.e., learn). Transparency of the agent's learning process will be manipulated by making it clear to the human how the information from human input is used (learning transparency: implicit, explicit, human-directed) in order to examine the effect on the human teammate and team performance.

2.2 Transparency

Knowledge of the agent's actions, its reasoning behind those actions, and the expected outcome of those actions can help the human teammate, improving task performance, SA, and reducing complacent behaviors, while not increasing their perceived workload [3, 4, 6]. Knowing what a machine agent is uncertain about can also improve human-agent team performance [5, 6]. Without knowledge of the agent's reasoning process, human operators may not know when the agent's planning is suboptimal for the mission's context. In this study, transparency of the agent's reasoning will be manipulated by the presence of icons displaying the five factors the agent evaluates when classifying a person as a potential threat or not (reasoning transparency: opaque, transparent) in order to examine the effect on the human teammate and team performance.

2.3 Workload

Mental workload has been described as "the relation between the function relating the mental resources demanded by a task and those resources available to be supplied by the human operator" [7]. Transparency of agent reasoning has been shown to improve task performance without increasing cognitive workload [4, 6], as such, its effect could be considered freeing resources so that more are available to accommodate task demands [8]. However, the influence of agent learning transparency on cognitive workload has yet to be examined. To that end, subjective workload measures will be used to inform as to the effect of learning transparency.

3 Current Study

In the current experiment, participants jointly conducted a threat classification task with a simulated learning-capable Aided Target Recognition (AiTR) agent while traversing a simulated urban environment. The agent identified persons that appeared along their route and classified each as either a potential threat or not. The agent either shared its reasoning for the classification in the robot dialogue window on the interface (transparent) or it did not (opaque). At times, the agent recognized a human or object, but was unable to classify it. When that occurred, the agent identified these potential threats and the participant would indicate yes/threat, no/nonthreat. The agent would share how the participant classification would be used to update its algorithm (explicit learning) or it would not (implicit learning), or the participant would specify what the missing information should be (human-directed learning). It is hypothesized that understanding how the agent used information supplied by the participant would result in improvements on the threat classification task and reduced cognitive workload [1, 9, 10], however when the participant had to direct learning it would increase workload.

Based on the review of the literature, the following outcomes are expected:

1. When agent reasoning is transparent, compared to opaque reasoning, there will be:

    a. Increased correct classifications on the threat classification task
    b. Increased time required to classify threats.
    c. Reduced participant perceived workload

2. When agent learning is explicit, compared to implicit learning, there will be:

    a. Increased correct classifications on the threat classification task
    b. Increased time required to classify threats
    c. Reduced participant perceived workload

3. When the human assists in agent learning, compared to explicit learning, there will be:

a. Reduced correct classifications on the threat classification task
b. Increased time required to classify threats
c. Increased participant perceived workload

4 Methods

4.1 Participants

Twenty participants ($Min_{age} = 18$ years, $Max_{age} = 28$ years, $M_{age} = 21.7$ years) received $15/h compensation.

4.2 Equipment/Simulator

A custom software application was developed in the UnReal 4 engine. The simulation was delivered via a commercial desktop computer system, two 15″ monitors, standard keyboard, and three-button mouse.

4.3 Study Design

This 2 (reasoning transparency; opaque vs. transparent) ×3 (learning transparency; implicit, explicit, human-directed) fractional factorial within-subjects study assesses the effects of transparency of agent learning (TAL) on a threat classification task. Since reasoning transparency and learning transparency are conveyed using the same icons, it is not possible to have transparent learning with opaque reasoning (see Table 1). In the baseline condition, Opaque Reasoning/Implicit Learning (TAL-1), the agent conducts the task without sharing its reasoning for unclassified persons. In the Transparent Reasoning/Implicit Learning (TAL-2) condition, the agent shares its reasoning but not indicate how the participant's input is used in updating its underlying reasoning; in the Transparent Reasoning/Explicit Learning (TAL-3) condition, the agent shares its reasoning and backfills reasoning information based upon participant input to indicate what it inferred from the human's input. Finally, in the Human-Directed Learning (TAL-4) condition, the agent shares its reasoning, and the participant completes any missing reasoning information before identifying whether the target is a potential threat. Participants completed four scenarios, one in each transparency combination condition.

Table 1. Reasoning by Learning Transparency condition matrix.

		Learning		
		Implicit	Explicit	Human-Directed
Reasoning	Opaque	TAL-1	--	---
	Transparent	TAL-2	TAL-3	TAL-4

4.4 Dependent Measures

Dependent measures are task performance (evaluated using number of correct classifications and response time), and cognitive workload (assessed using the NASA-TLX raw scores).

4.5 Procedure

Upon arrival, participants signed the informed consent form, and then completed the demographics questionnaire and a brief Ishihara Color Vision Test [11]. Training lasted approximately 30 min, and consisted of self-paced PowerPoint slides, several assessments and a training scenario. Participants were required to achieve at least 80% proficiency on the assessments to continue.

The study session began immediately after the training session and lasted approximately 2.5 h. Participants completed four scenarios, one in each transparency condition assigned to one of four potential routes. The scenarios were presented in order of increasing transparency (i.e., TAL-1, TAL-2, TAL-3, and TAL-4); however, the route assignment was counterbalanced and randomized. After each scenario, participants completed a NASA-TLX questionnaire assessing their cognitive workload. Following completion of all scenarios, participants were debriefed and dismissed.

5 Results

Data were analyzed using repeated-measures ANOVAs ($\alpha = .05$) and planned comparisons (TAL-1 to TAL-2, TAL-2 to TAL-3, TAL-3 to TAL-4). Means and Standard Deviation (SD) are shown in Table 2.

Table 2. Means and Standard Deviation for Performance and NASA-TLX factors.

		TAL-1		TAL-2		TAL-3		TAL-4	
		M	SD	*M*	SD	*M*	SD	*M*	SD
Performance Measures	Correct Class %	91.4	4.7	93.8	3.8	94.4	3.1	93.7	3.8
	Response Time	11.5	4.2	9.9	2.6	8.3	1.4	21.2	19.0
NASA-TLX scores	MD	69.3	26.7	59.3	25.6	55.0	24.7	67.3	24.0
	TD	61.0	26.5	56.0	24.1	51.0	27.6	70.5	19.0
	PD	34.8	27.4	32.8	27.1	33.8	26.4	37.0	28.8
	Effort	65.8	15.2	54.0	24.3	51.8	21.4	66.8	21.0
	Frustration	38.5	29.1	32.3	25.1	29.8	23.6	38.3	26.7
	Perf. Satisfaction	32.5	21.4	33.5	22.0	26.8	17.9	41.0	23.8
	Overall	50.5	16.4	44.6	17.6	41.5	16.8	53.5	16.9

Note: MD - Mental Demand, TD - Temporal Demand, PD - Physical Demand

5.1 Correct Classifications

Agent transparency had a marginally significant effect on correct classifications, Wilkes' $\Lambda = 0.658$, $F(3,17) = 2.94$, $p = 0.063$. Examination using planned comparisons show that while agent reasoning transparency had a significant effect on correct classifications (Cohens $d_s = 0.56$), learning transparency did not.

5.2 Response Times

Both reasoning and learning transparency affected the participants response time, Wilkes' $\Lambda = 0.463$, $F(3,17) = 6.56$, $p = 0.004$. Time to respond decreased as transparency increased; it was longer in TAL-1 than in TAL-2 (Cohens $d_s = 0.44$), and longer in TAL-2 than in TAL-3 (Cohens $d_s = 0.78$). However, time to respond increased dramatically from TAL-3 to the Human-directed Learning condition TAL-4 (Cohens $d_s = 0.96$) See Fig. 1.

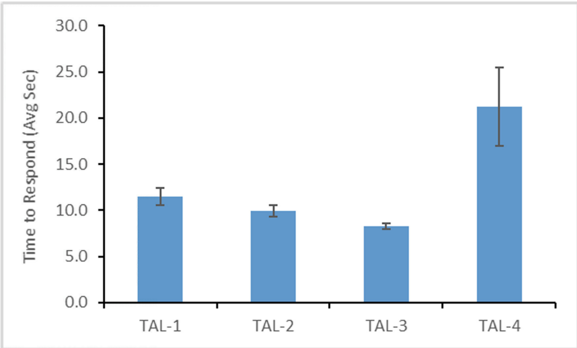

Fig. 1. Response Times in average seconds by transparency condition.

5.3 Workload

Overall, transparency level did have a significant effect on participant workload, Wilkes' $\Lambda = 0.451$, $F(3,17) = 6.91$, $p = 0.003$ (see Fig. 2). Access to agent reasoning (TAL-1 to TAL-2) reduced Mental Demand scores, (Cohens $d_s = 0.38$; $F(1, 19) = 8.54$, $p = 0.009$) and Effort scores (Cohens $d_s = 0.58$; $F(1, 19) = 7.08$, $p = 0.015$). Access to learning transparency (TAL-2 to TAL-3) did not affect most workload factors, except for an increase in performance satisfaction (as indicated by lower scores, Cohens $d_s = 0.34$; $F(1, 19) = 8.60$, $p = 0.009$).

Human-Directed Learning (TAL-4) increased workload and decreased performance satisfaction, as compared to Explicit Learning Transparency (TAL-3). Mental Demand (Cohens $d_s = 0.50$; $F(1, 19) = 11.47$, $p = 0.003$), Temporal Demand (Cohens $d_s = 0.82$; $F(1, 19) = 15.72$, $p = 0.001$), Effort (Cohens $d_s = 0.71$; $F(1, 19) = 29.48$, $p < 0.001$), and Performance Satisfaction (Cohens $d_s = 0.68$; $F(1, 19) = 19.47$, $p < 0.001$) scores all increased dramatically in TAL-4 as compared to TAL-3.

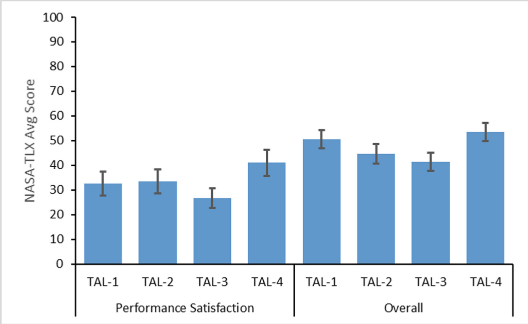

Fig. 2. Performance Satisfaction and Overall NASA-TLX scores.

6 Discussion

The goal of this study was to examine how transparency of agent reasoning and agent learning interact to influence the human's task performance. Transparency of agent reasoning is well known to support improved task performance in human-agent teaming without concomitant increases in perceived workload [5, 6, 10], and this study adds more evidence to support that position. What is still unknown is how transparency of agent learning affects the human-agent team's task performance.

This study examined a scenario that is very likely to become a reality in the near future – a human teaming with a learning capable agent that collects information from the human and uses that input to update its algorithms later. There was no difference in correct classifications due to learning transparency. There are several potential explanations for this result. First, the task itself was not difficult; each encountered person was visible and unobstructed for a minimum of 6 s and snapshots were provided for later review. Second, the agent classified most persons prior to the participant classifying, so it would be easy for the participant to agree with the agent's classification. However, correct classifications were expected to drop off in the human-directed learning condition because of the increase in task demand, so the consistency in performance is surprising. Reviewing the associated response times, it appears there was a speed-accuracy trade-off [13] in this condition.

Increased learning transparency reduced task completion time and perceived workload in the explicit learning condition, demonstrating that understanding how the agent is using the humans input can be beneficial. However, burdening the human with directly teaching the agent resulted in dramatic increases in task completion times and perceived workload, with a concomitant decrease in task performance satisfaction. An increase in response time was expected; when reasoning was missing, the participant had to supply the needed information. However, the amount of increase was surprising, as response times more than doubled those in the explicit learning condition. Clearly, there is more happening in this condition than an extra mouse click or two. These findings indicate that when teamed with learning capable agents, human performance and workload are best supported when the autonomy can derive its needed information with minimal human direction.

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Examining Vigilance in a Simulated Unmanned Aircraft System (UAS) Monitoring Task

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Abstract. Tasks which require individuals to sustain attention to seldomly occurring stimuli for long periods of time can induce workload, stress, and often lead to the vigilance decrement [4, 10]. Research into potential methods to mitigate the effects of these tasks have proposed training, video game experience, and the potential of using music. This study examined the impact of listening to music during performance of a simulated UAS monitoring task on the vigilance decrement using twenty-eight participants from a southeastern private Florida university. Music was not found to relieve the vigilance decrement, however, interesting results were found related to gaming experience and workload. Findings were consistent with increased workload and mental demand for participants with gaming experience. These findings are discussed in the context of operator selection.

Keywords: Workload · Sustained attention · Mental demand · Operator selection

1 Introduction

Several modern operational tasks, such as Unmanned Aerial Systems (UAS) monitoring tasks, require sustained attention, as the operator must focus on a task for long periods of time [5, 10]. Tasks which require sustained attention, such as a UAS pilot's monitoring task, are a prime example of a typical vigilance task, as they require individuals to detect signals that are seldom and challenging to identify [10]. Studies have revealed that people are not able to sustain the same level of attention for long periods of time without a decrease in attention [8, 15, 22]. This decrease in an individual's capacity to sustain attention at an effective level typically surfaces after approximately thirty minutes and is referred to as the vigilance decrement [23]. High stress and workload are commonly cited as a byproduct of sustained attention tasks and can cause personnel retention issues [7, 9, 10, 28]. Increased workload has been found to be due to the pressure of staying attentive without a high task load [10, 31]. Given ongoing issues with recruitment and retention for the U.S. Air Force's UAS workforce [3] understanding how to ameliorate negative byproducts of vigilance is important.

Research has shown that there are individual difference factors that influence the ability to sustain attention. Specifically, video game players (VGP) have been found to have improved cognitive functions that are important to vigilance tasks, such as spatial ability, attention allocation skills, and rapid target identification [1, 9, 24]. However, it

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is important to note that the lack of excitement and interactivity during a vigilance task, may yield differences in workload and mental demand for VGPs as, compared to non-gaming populations [18, 26, 29]. Studies looking into methods to combat the vigilance decrement have proposed the inclusion of music during task performance to increase arousal [12, 19]. Positive valence music that participants like has been found to lead to positive performance in the form of decreased misses in a sustained attention to response task [2]. Further, several studies have found support for music increasing arousal [5, 20, 32]. Per and Zhang [24] examined the effects of music on a simulated strategy game and found that music had a significant benefit to proactive control while those who played the simulated strategy game without music had significant improvements to reactive control. A study by Navarro et al., [20] found that music led to increased arousal and better driving in a driving simulator. Studies have also found that music can lead to distraction and increased reaction times due to arousal or relaxation caused by the music [6, 19]. Given the rise in human performance tasks that require sustained attention (e.g., UAS inspections and surveillance), identifying factors which may overcome the vigilance decrement is important, including obtaining more conclusive evidence regarding the use of music to achieve this. This study examined the impact of listening to music during performance of a simulated sustained attention UAS task, on target detection performance, stress and workload. Additionally, the effect of individual differences related to prior UAS experience and gaming experience were examined. This paper describes the methods, results and implications of the experimental findings.

2 Methods

Participants. Twenty-eight participants from a southeastern private Florida university performed a simulated UAS monitoring task. Participants were recruited using a University list service. Inclusion criteria included normal color vision. Participation was voluntary and the study was approved by a university Institutional Review Board. Participants were entered into a raffle to win a $100 gift card; some received extra credit.

Experimental Design. The study was a between groups, randomized posttest only control group experimental design. The independent variable was presence of music during task performance (present vs. not). There were three dependent variables: performance, stress, and workload. Participants were assigned to groups using a latin squares method. It was hypothesized that those who received music during task performance would have (a) better performance, (b) lower workload levels, and (c) lower stress levels compared to those who performed the task with no music. Additionally, an exploratory analysis was conducted to examine the impact of UAS and gaming experience.

Music. A playlist of nine songs was created on Spotify and played for participants in the music group. The music selected followed criteria for positive-valence, slow-tempo songs, which have been found to promote vigilance and performance [2]. Valence is defined here as the emotion emitted or perceived by the song. Positive valence was measured using the Positive and Negative Affect scale (PANAS) [30]. A group of four students varying in age and gender rated 40 songs for their affect level. Songs which scored in the top quadrant for valence were assessed for slow tempo (i.e., in the range of 50 to 100 beats per minute (bpm). Songs not in the 50 to 100 bpm, based on the bpm calculation software, GetSongbpm, were removed from the playlist.

Measures. Target detection was measured as either a "hit" (i.e., correct detection) or a miss (i.e., target not detected). Each correct detection input was recorded in the software output log with a timestamp, allowing for the calculation of reaction time, which was calculated as the difference between the time in which the UAS became visible on the screen and when the participant hit the space bar. A post-experiment survey was administered after the study via Qualtrics and included demographic information such as gender, age, academic level, gaming experience and UAS experience. Workload and its subscales of mental demand, physical demand, temporal demand, performance, effort, and frustration level were also measured post-experiment using the NASA-TLX short, a 6-item, 20-point scale, from low to high.

Additionally, despite attempts to equalize target difficulty, a pilot study using four participant's revealed variability across target detection and reaction time as well as target difficulty ratings for all targets. Therefore, a difficulty scale was included in the study to allow difficulty to be taken into account during analyses. To rate difficulty, after task performance, participants re-watched the points in the simulation where the UAS came onto the screen then rated the difficulty of each target on a 5-point scale (1 = very easy and 5 = very difficult). Additionally, participants in the music group were administered the PANAS, a validated measure of evoked positive emotion, after testing to rate the song playlist for positive affect [11].

Procedure. When participants first arrived, they reviewed the consent form followed by a pre-survey. Once completed, they were given details about how to perform the simulated task. After the scenario and instructions were read aloud, participants were presented with a piece of paper showing an example of the Heads Up Display (HUD) information they would be seeing on the screen. The illustration showed where the information needed to perform the task was located, including the altitude of the UAS, and what the target UAS looked like. Participants in both the music and non-music conditions were then fitted with MDRZX110NC SONY headphones which had 13 dB of noise suppression. At this time, participant's in the music condition were told they would be listening to music during the task and set a comfortable music volume as a song played. After selecting the volume, they were then asked to remove the headphones until the simulation commenced. Both groups were given time to ask questions and instructions were repeated. The participant then performed a 31-min sustained attention task, in which they monitored a video presenting a landscape from a simulated UAS first-person view. Two inputs were required from the participant, to hit space bar when seeing the UAS and type the number 1 into a document located on a separate laptop, when the UAS rose above an altitude of 100 AGL. The simulated task followed parameters set by Daly et al., [7] as closely as possible, on how to develop a laboratory vigilance task for a UAS environment. Therefore, the target (i.e., a covert UAS) was presented seven times within the span of the 31-min simulation of a barren junkyard that could be circled by the UAS in approximately five minutes, ensuring that the changing environment did not appear novel. Knowledge of results feedback was incorporated through a window that appeared stating: "Target identified!" if space bar was selected and the UAS was on the screen.

If the UAS was not in sight and the space bar was hit a prompt displaying: "Target not in sight!" appeared. After the simulation ended, participants were asked to complete the post survey and re-watch the areas in the simulation where the target was present to rate each target's difficulty.

3 Results

Preliminary Analysis. Three participants were excluded from the analysis, as two were unable to complete the study due to time constraints, and the third participant had a personal issue which required the study to be stopped. This resulted in 25 participants' data being included in the analysis. Participant's target difficulty ratings were examined using a 2 x 7 (music x target) repeated-measures ANOVA. Results of repeated-measures revealed a significant main effect of target on difficulty ratings, (F (6, 18) = 21.633, $p >$ .001, partial $\eta^2 = .878$. There was no significant main effect of music on difficulty ratings, (F (1, 23) = .041, $p >$ .05, partial $\eta^2 = .054$. There was also not a significant interaction between target and music for difficulty ratings, F (6, 18) = 1.367, $p >$ .05, partial $\eta^2 = .313$. These results reveal that, despite our efforts to ensure consistent difficulty, there was a significant variation in difficulty across targets, and this was consistent across both treatment conditions. As such, the variability in target difficulty resulted in a confounding variable. To account for this, the decision was made to focus the repeated measures analyses on the last four targets as they all had target difficulty greater than two and a half and all took place after approximately 15 min, when the vigilance decrement has the potential to commence.

Primary Analysis. A 2 x 4 (music presence x target) repeated-measures MANOVA was conducted on measures of target detection and reaction time, to examine the impact of music on performance. At the multivariate level, there was not a significant main effect of music presence, $F(2, 22) = 1.276$, $p > .05$, partial $\eta^2 = .104$. However, within subjects, there was a significant main effect of target, $F(2, 22) = 41.218$, $p < .001$, partial $\eta^2 = .932$. There was also a significant interaction between music presence and target, $F(2, 22) = .2.651$, $p = .05$, partial $\eta^2 = .469$. Univariate results revealed that there was a significant main effect of target on detection, F (1, 23) = 6.526, $p = .001$, $\eta^2 = \cdot 221$ and reaction time $F(1, 23) = 19.288$, $p < 001$, $\eta^2 = .456$. There was not a significant effect of music on detection $F(1, 23) = .270$, $p > .05$, $\eta^2 = .012$ or reaction time, $F(1, 23) = 2.064$, $p > .05$, $\eta^2 = .082$. There was also not a significant interaction between target and music on detection, $F(1, 23) = 1.543$, $\eta^2 = .063$ or reaction time, $F(1, 23) = .926$, $\eta^2 = .039$.

An ANCOVA examining the influence of music on workload with a covariate of gaming experience was conducted. There was not a significant interaction between music presence and gaming experience, F(3, 21) = 1.983, p = .1474. There was, however, a significant effect of gaming experience on workload, F(2, 2) = 4.80, p = .03. To examine whether music that evoked emotions could have had a relationship with workload, correlational analysis of affect scores, overall workload, and the workload subscales was conducted. A positive significant relationship was found for positive affect and mental demand, r = .54, p = .05.

To examine the potential impact of individual difference factors, a correlation analysis was conducted including: gaming experience, UAS experience, workload and each workload subscales. Gaming experience was significantly and positively correlated with the mental demand subscale of the NASA TLX, $r = .60$, $p < .001$. Gaming experience was significantly and positively correlated with the effort subscale of the NASA TLX used to measure stress, $r = .53$, $p < .01$. Gaming experience was significantly and positively correlated with overall workload measured by the NASA TLX, $r = .46$, $p < .05$. Results revealed that as gaming experience increased, mental demand, stress, and overall workload also increased. However, no significant correlation was found for UAS experience, physical demand, temporal demand, or frustration. In order to examine the effects of gaming, t-tests with unequal variances were used to compare the means with respect to the variables [13]. A two samples t-test assuming unequal variances was conducted comparing the mental demand of those with low gaming experience to those with high gaming experience. Mental demand was significantly different between these groups, $t(22) = 4.35$, $p = .0002$. A two samples t-test assuming unequal variances was conducted comparing the effort of those with low to those with high gaming experience. Effort was significantly different between these groups, $t(20) = 3.26$, $p = .004$. When examining the means, those with high gaming experience scored the task on average 4.1 points higher on the effort domain than those with low gaming experience. A two samples t-test assuming unequal variances was conducted comparing the workload of those with low to those with high gaming experience. Workload was significantly different between these groups, $t(16) = 2.390$, $p = .0294$.

4 Discussion

This study aimed to address whether music could be a viable mitigation technique to prevent the vigilance decrement. The vigilance decrement is characterized by an increase in reaction time, over time, and a decrease in detection [8, 14]. No significant difference in reaction time between music and non-music groups was found. Due to the similarity in the reaction time trends for both the music and non-music groups, it appears that the addition of music did not affect reaction time. However, the variability in difficulty across targets could be to blame. Target difficulty for the simulated vigilance task should have been equivalent across targets to facilitate the identification of the treatment effect [7]. The significant variation in difficulty may have washed out any treatment effects or the increase in difficulty in the last 15 min (i.e., target 4 and on) may have prevented a vigilance decrement altogether. Difficulty has been found to lead to stimulation [17, 25]. A study by Thomson et al., [27] found that varying task difficulty can alleviate performance degradation in the vigilance task. Furthermore, the simulation may not have been long enough to create a vigilance decrement [5, 8], as other simulated UAS tasks measuring the effects of performance have been longer [5, 7].

No significant difference in target detection between music and non-music groups was found in the analyses when attempting to account for difficulty by examining detection in the last four targets. Interestingly, the music group had a higher detection trend until the sixth target where there was a large decrease in detection, however, detection increased again after the sixth target. It is not clear why there is such a discrepancy.

A potential reason could be the song being played before target 6 may have been too arousing, to the point of distraction. Previous studies have found that music can lead to distraction in vigilance scenarios such as driving [6, 21]. A study by North and Hargreaves [21] found that arousing music can compete with cognitive processing and lead to performance decrements. Music may aide in detection as long as difficulty is not too high, at which point it becomes a distraction. Additionally, when examining the music affect scores, the higher the evoked positive emotion the higher the mental demand scores. This may have played a role. Some of the music may have led to increased mental demand rather than alleviating the mental demand, thus muddying the waters.

Both groups had perfect detection for the final target. The trend for the participants in the non-music group seemed to stay constant until the final target. The perfect detection ($M = 1.0$) of the final target may been due partially to a ceiling effect, which may have led to inaccuracy in the data. However, another reason that the average rating did not fall under "very easy", is due to knowledge of the study coming to an end, leading to an increase in arousal. Malhotra [16] found that when a challenge is nearing its end participant's arousal levels sometimes increase as they attempt to finish strong.

There were some interesting findings with respect to some of the individual difference variables. When examining the relationship between music and mental demand with a covariate of gaming, it appears that gaming did not make any difference in the amount of mental demand experienced between groups. However, when looking solely at gaming experience, it did have an effect on workload. Those who had high gaming experience self-reported higher workload and mental demand than those with low gaming experience. These findings could be helpful to narrowing down good candidates for UAS operators. Although performance was not significantly different, studies have found that high workload is negatively correlated with retention and job satisfaction [33]. Those with high gaming experience may potentially be more likely to leave the job than those who have low gaming experience. Additionally, given that retention is an issue for certain UAS domains [3], finding ways to select candidates which would potentially pose less retention issues would beneficial.

5 Conclusion

Although the findings with respect to music alleviating the vigilance decrement were inconclusive, there were several limitations of the study that could have prevented conclusive results emerging. First, the variability in difficulty could have led to arousal, preventing the vigilance decrement, the ceiling effect, and leading to the variability seen in reaction time for certain targets. Second, the novelty of the simulation may have prevented the vigilance decrement from appearing. Future research should attempt to ensure that difficulty is held constant across targets and extend the length of the study to counteract the novelty effect. Interesting results were found with respect to gaming experience, workload, effort, and mental demand. Results indicated that gaming experience is positively correlated to workload, mental demand and stress, therefore indicating those with high gaming experience may also experience higher workload, mental demand, and stress. This may not be ideal for tasks requiring sustained attention. These findings could have implications for job selection parameters for roles which require sustained attention, such as, UAS operations and air traffic control, leading to more optimal employee