Measuring Fatigue Dynamics of Augmented Reality in the Digital Learning Era Using Motion Capture Data

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Abstract. In this digital learning era, Augmented Reality (AR) has become a significant driver of innovative user experience. However, the ergonomic implications of AR, particularly regarding the postural fatigue dynamics, have not been comprehensively addressed. This study investigates the correlation between prolonged AR engagement and the onset of postural fatigue, characterized by a backward shift in the center of mass (COM). Employing motion capture technology alongside cognitive load assessment tools such as the NASA Task Load Index and HoloLens eye-tracking, we seek to quantify the relationship between user posture, engagement duration, and perceived workload. We hypothesize that an observable rearward displacement of COM signifies escalating fatigue levels. The methodology integrates ergonomic analysis, biomechanics, and predictive modeling. Preliminary findings indicate a decline in postural stability with increased AR exposure, reinforcing the need for ergonomics interventions. This study underscores the necessity of ergonomic consideration in the design and use of AR systems to safeguard user well-being in educational settings.

Keywords: Augmented Reality · Motion Capture · Predictive Analysis · Data Analysis

1 Introduction

The ascent of AR as a cornerstone of modern technological advancement is rooted in its rich history of development. From its early inception as a novel concept in the 1960s to its sophisticated implementation in contemporary devices [1], AR has consistently

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expanded the horizons of user interaction. Despite its prolific growth, the intersection of AR and ergonomics [2] and workload remains a nascent area of inquiry. The implications of AR on society are manifold. In educational settings, AR presents opportunities for immersive learning [3] but also poses possible workload effects during prolonged use [4]. In healthcare, AR can transform patient care yet may also contribute to professional fatigue if ergonomic risks are not mitigated. The entertainment industry, meanwhile, thrives on the allure of AR's immersive experiences but seldom acknowledges the potential for user discomfort and strain. It is within this broader societal context that our research acquires its urgent relevance.

Our hypothesis posits that prolonged engagement with AR technology induces fatigue and tiredness in users, a phenomenon that can be observed and quantified through motion capture data. We theorize that as users interact with AR over extended periods, there will be discernible changes in their physical movements and postures, indicative of increasing fatigue levels. Our study aims to thoroughly test this hypothesis, seeking to establish a clear link to the ergonomic behavior of AR exposure.

Our approach to studying fatigue dynamics in AR involves drawing from deep interdisciplinary knowledge. We apply biomechanical principles to analyze the subtle nuances of human movement within AR environments. Through motion capture technology, we glean high-fidelity data that reveal the intricacies of human posture as users engage with AR. Concurrently, physical load informs our use of the NASA TLX [5], allowing us to map the workload placed on users during AR tasks [6]. The inclusion of eye-tracking data from HoloLens devices adds a layer of depth to our understanding of user engagement, enabling us to correlate visual attention to direction with postural changes.

Our initial findings show the trend toward decreased postural stability during AR learning. This study enables us to quantify the dynamics of fatigue experienced during AR learning by utilizing motion capture data. Through this approach, our objective is to concentrate on significantly enhancing user comfort and safety in the development of upcoming AR learning settings.

2 Methodology

2.1 Experimental Design

In this study, a quasi-experimental design [7] was utilized to assess an Augmented Reality (AR)-based interactive learning system, specifically tailored to augment engineering education [8–11]. This innovative system comprised fifteen 3D scenes, thoroughly crafted in Unity. These scenes were split across two biomechanics lectures, with seven scenes in the first lecture and eight in the second. Intriguingly, the lectures were displayed on Microsoft HoloLens 2, where scenes would dynamically pop up based on the participant's location, pre-configured with a naming convention numbered from 1 to 8 to facilitate easy navigation and association. They were presented on a semi-circular virtual blackboard, forming part of an immersive learning environment. This environment was organized into five distinct panels: Central, Left-central, Right-central, Left, and Right. Each panel displayed unique information, contributing to a comprehensive educational experience, encompassing teaching methodologies, problem-solving techniques, and visual representation of concepts as shown in Fig. 1.

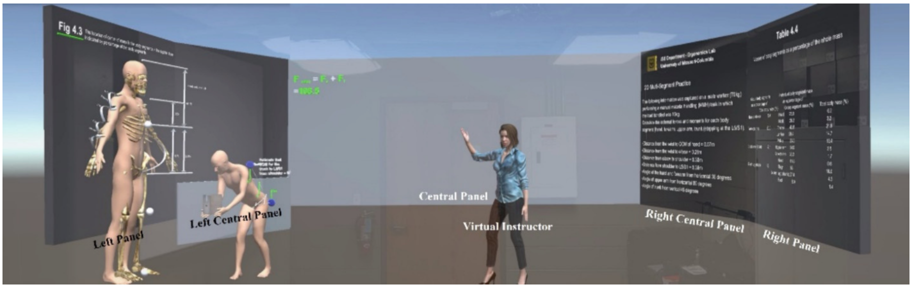


Fig. 1. Labelled 3D scene of an AR module built with unity.

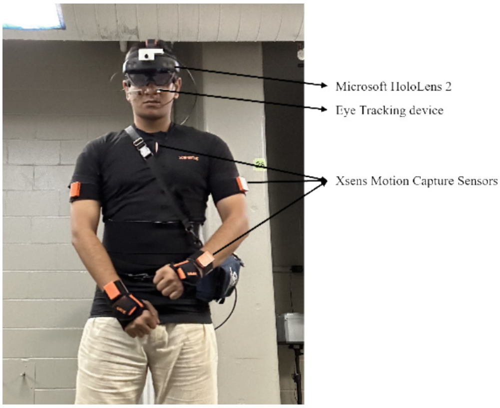


Fig. 2. Equipped Hardware components.

Participants in the study were equipped with advanced technological tools, including the Microsoft HoloLens 2 [12], Xsens Motion Capture sensors [13], D-lab Eye Tracking (see Fig. 2), and a screen to display questionnaires. The experiment also featured Location Tracking, which was attached to the participants' tables. These tables are designated for placing laptops that contain experimental questionnaires. Prior to the commencement of the experiment, participants underwent a thorough orientation session, which involved a training module designed to acquaint them with the experiment's components and processes.

The AR system's features were notably advanced. A 3D animated virtual instructor, powered by the Xsens motion capture system and Murf AI, facilitated realistic movements and natural-sounding voice synthesis. The Microsoft HoloLens 2, enhanced with the Microsoft Mixed Reality Toolkit 3, enabled spatial interactions and eye-tracking, capturing crucial data like user gaze points and interaction times with virtual objects. Spatial navigation and AR scene activation were adeptly managed using the Q-Track NFER system [14], which included a router, locator receiver, positioning sensor, and software. This setup allowed the system to respond dynamically to the user's real-time location. In place of traditional paper-based methods, an online questionnaire system was integrated into the AR environment, ensuring an uninterrupted user experience.

The study's participants consisted of 21 undergraduate engineering students. They received comprehensive training on using the HoloLens and navigating the AR environment. Each Unity scene, corresponding to a specific lecture segment, was deployed as an independent AR application. Participants navigated through these scenes, with the system tracking their location and gestures (recognized via Xsens motion capture data) used for system navigation and interaction.

2.2 Data Collection

This section details the collection of various types of data essential for the study. It includes the process of capturing eye-tracking data using Microsoft HoloLens 2 to analyze participants' visual engagement with the AR content, motion capture data using the Xsens system, which played a pivotal role in collecting precise data on participants' physical movements, and performance data from the post-assessment questionnaire providing critical insights into the learning outcomes and effectiveness of the AR system.

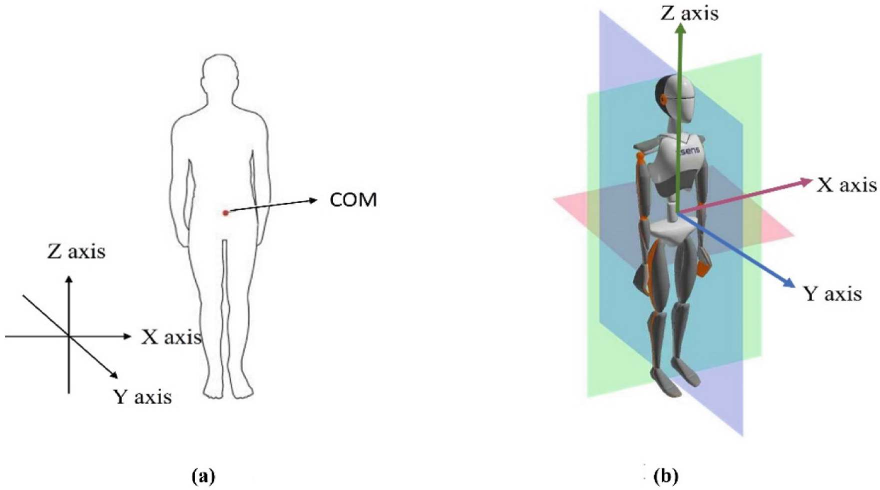
3 Data Analysis

3.1 Postural Dynamics Analysis

The Analysis of Postural Dynamics provided a detailed insight into how participants physically interacted with the AR modules. Through the detailed visualization of Center of Mass (COM), which is a theoretical point where the total mass of the body is concentrated [15], and coordinates across various modules, we could discern the subtleties of balance and stability affected by the AR experience [16, 17] (Fig. 3).

Utilizing the motion capture data, we plotted the deviations of the individual's COM positions (x, y, z) from the overall average for each module. Plots (see Fig. 4) illustrated these deviations, showing a clear variance in participant postures across different modules. For instance, the deviations in the 'COM pos x' occasionally showed a substantial divergence from the average, suggesting lateral shifts in balance that could indicate a reaction [18] to the content or an ergonomic response to the AR environment. Additionally, we plotted the COM position against time for each axis (x, y, z) in a series of line graphs. These plots revealed patterns over time, such as whether there was a trend towards increased deviation, which might be associated with fatigue or discomfort as the participants progressed through the modules.

To explore the link between physical demand and variations in the COM, the study compared the deviations of the COM from a baseline posture for each module. This baseline posture refers to the initial stance of the participant when they begin interacting with the AR module. It supported a deeper analysis of postural dynamics, offering quantifiable evidence of how the AR system impacted physical engagement. Variations in COM deviations suggested that certain modules may impose more physical demands on participants, leading to more pronounced postural adjustments.



(a) A figure showing the position of the COM (b) Three anatomical planes of the human body

Fig. 3. Demonstration of COM.

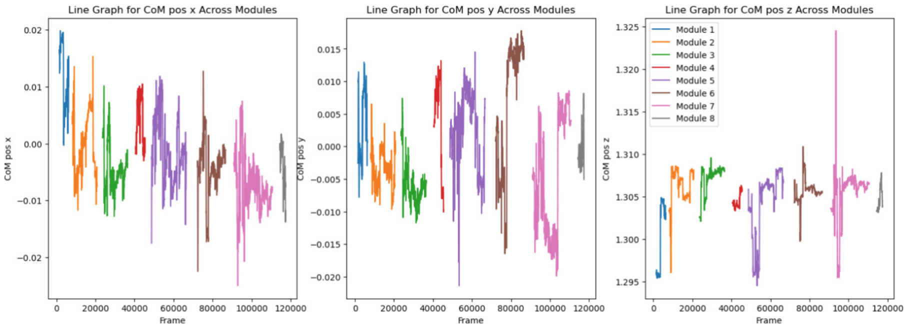


Fig. 4. Initial COM analysis Visualizations in three axes of moment.

3.2 Slouching Scores Analysis

In this study, we implemented slouching scores as a quantitative method to assess fatigue dynamics within AR environments. This metric was designed to evaluate the postural changes experienced by participants engaged during the experiment (Eq. 1). The slouching score is a numerical indicator ranging from 0 to 100, which calculates the extent of a participant's postural deviation from an initial posture. If a slouching score is 100, it means that no deviation from the initial posture, representing no physical fatigue, whereas lower scores indicate higher physical fatigue.

$$Slouching\ score = 100 \times (1 - (\frac{abs(COM\_pos\_X - Global\_Baseline)}{Maximum\_Deviation})) \quad (1)$$

The calculation of slouching scores was based on the establishment of an initial posture. This baseline was derived from the average position of the COM in the x-direction ('COM pos x') during the first 4 s of the beginning of AR learning lecture represented by the dotted line in Fig. 5. We determined that within the first 4 s, participants were stable across multiple observations, making this time frame suitable for establishing a neutral or standard posture for each participant. Following the establishment of this baseline, the analysis proceeded with the computation of the maximum deviation from the baseline. This was achieved by isolating the maximum deviations in 'COM pos x', representing the most significant shifts from the initial posture. To synthesize the data, we computed the average slouching score for each 60-frame segment within each module. This averaging was crucial to smooth out anomalies in individual frames, providing a clearer picture of the overall postural dynamics throughout the AR interaction. By focusing on these averages, the analysis could reveal broader patterns and trends that might be obscured in a frame-by-frame examination. Figures 4 and 5 was a representation of a single participant, while other participants followed a similar trend.

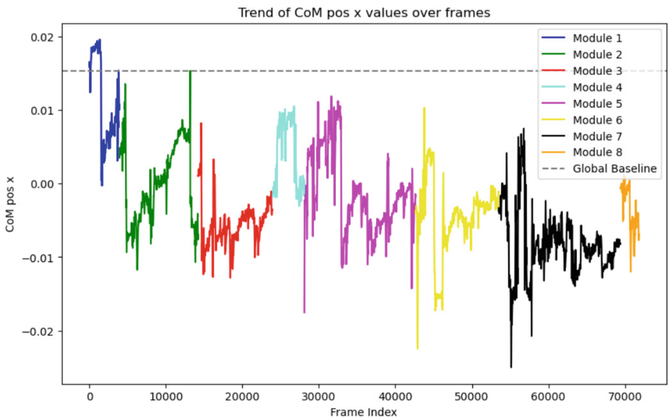


Fig. 5. Frame-by-Frame COM pos X Trajectory Across Modules

To confirm the relationship between these average scores and the physical demand experienced by participants, we planned to compare them with the NASA TLX Physical Demand (PD) values. The NASA TLX is a subjective assessment tool that measures the perceived physical strain and workload experienced by an individual. Each subscale in the NASA TLX, including the PD, is rated on a scale from 0 to 100, where 0 indicates very low demand, and 100 indicates very high demand. This comparison is aimed at establishing a correlation between the objective postural data (quantified by slouching scores) and the subjective perception of workload and physical demand (as measured by NASA TLX). For instance, a high slouching score, close to 100, would typically be expected to correspond to a lower NASA TLX PD value, indicating minimal perceived physical strain. This is because a slouching score of 100 signifies no deviation from the baseline posture, implying an ergonomically sound and comfortable position for the participant. Conversely, a lower slouching score, indicating a greater deviation from the baseline posture and potentially more ergonomic strain, would correspond to a higher NASA TLX PD value. This correlation would suggest that as participants experience more significant postural changes (as reflected in lower slouching scores), they also perceive a higher level of physical demand and strain during their interaction with the AR system.

4 Results

4.1 Slouching Scores

Our findings demonstrated a consistent trend across the participant group – a gradual decline in slouching scores calculated by using COM pos X values across all modules. According to our Hypothesis, this declining trajectory of scores suggests an escalation in postural deviation, due to increasing fatigue and physical demand experienced by participants as they engaged more extensively with the AR modules. For example, observing a participant's slouching score decrease from 100 in the first module to 70 in the last module illustrates a significant 30-point reduction. This reduction aligns with a corresponding 30% increase in perceived physical demand, as reflected in their NASA TLX Physical Demand (PD) values. A critical observation from our analysis was the alignment of data from 11 out of 16 participants with the hypothesized model. This alignment indicates a notable correlation between the decrease in slouching scores and an increase in physical demand over the progression of modules as shown in Table 1.

Table 1. Table showing Data of Average slouching scores across modules and NASA TLX PD values of participants.

1	2	3	4	5	6	7	8	NASA TLX PD	Approx Difference
63	65	48	53	30	25	35	29	70	71
69	64	71	84	67	77	60	67	1	33
92	96	89	62	64	85	58	67	40	42
83	88	86	87	86	83	69	92	60	32
94	84	88	74	86	83	91	89	10	11
95	80	72	76	72	59	66	61	10	39
97	91	83	87	90	84	88	81	60	19
85	84	86	87	80	62	44	60	50	55
94	80	58	53	66	64	63	76	10	24
89	87	87	76	86	87	78	76	20	24
86	81	62	46	50	48	65	54	55	46
89	83	89	77	85	78	71	79	1	21

(*continued*)

Table 1. (*continued*)

1	2	3	4	5	6	7	8	NASA TLX PD	Approx Difference
97	96	92	97	90	95	94	66	60	34
82	63	62	67	58	59	53	26	10	75
91	89	88	89	90	89	87	87	80	13
82	57	41	67	53	44	34	47	50	53

The data in Table 1 delineates the average slouching scores across eight modules for selected participants, along their corresponding NASA Task Load Index Physical Demand values. The 'Approx Difference' column calculates the deviation of the last module's slouching score from the maximum possible score of 100, providing an indicator of the change in posture over the course of the modules.

4.2 Regression Model

The linear regression model allowed us to predict Physical Demand (PD) values for each participant, based on their slouching scores across AR modules. This led us to a comparison between the actual NASA TLX PD values and the predicted PD values obtained from the regression model.

Table 2. Tabular chart showing Regression Coefficients for slouching scores by AR modules.

Slouching scores	Regression Coefficients	Std Error	t Ratio	Prob > |t|
Intercept	−22.70897	50.14632	−0.45	0.6595
Module 1	−2.034923	0.752309	−2.70	0.0205*
Module 2	4.3616112	1.018101	4.28	0.0013*
Module 3	−2.883978	0.779677	−3.70	0.0035*
Module 4	1.3736066	0.502748	2.73	0.0195*

Table 2 reveals that the slouching scores for the first four AR modules (1, 2, 3, 4) are significantly correlated with the NASA TLX Physical Demand (PD) values. For modules 1 and 3, the negative coefficient suggests that increased physical demand leads to higher postural deviation. Conversely, for modules 2 and 4, the high physical demand results in lower postural deviation.

The scatter plot shown in Fig. 6 compares the actual NASA TLX Physical Demand (PD) scores with the PD scores predicted by our regression model. Each point in the graph corresponds to a pair of actual and predicted PD scores for an individual participant. R-squared value is 0.64. It means that approximately 64% of the variability in actual NASA TLX PD scores can be explained by our linear regression model. Also, the P-value is

0.0166. It implies that the model has a good predictive power and that the relationship between the actual and predicted values is statistically significant.

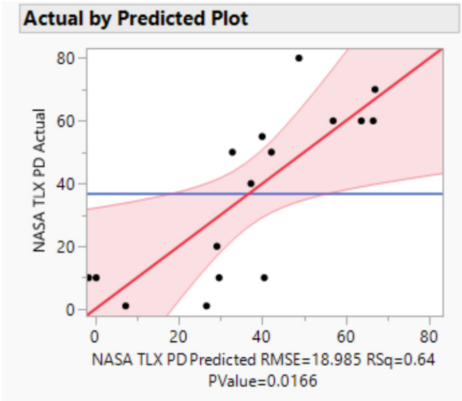


Fig. 6. A Scatter plot comparing actual NASA TLX PD values against predicted PD values.

From all the above results we can understand this is a good fit model and demonstrates robust performance. To support this analysis, we did correlation analysis between NASA TLX PD values and the Predicted PD values. The result shows 0.8114 (see Table 3), which is a high correlation between them. It suggests that the model's estimates are closely aligned with actual data. A correlation above 0.8 is considered indicative of a strong relationship, meaning that the model's predictions are likely to be consistent and reliable.

Table 3. Correlation Matrix of Actual vs. Predicted Nasa TLX PD Scores.

	NASA TLX PD	Predicted PD
NASA TLX PD	1.0000	0.8114
Predicted PD	0.8114	1.0000

5 Discussion

While AR's potential for creating immersive and interactive experiences is widely recognized, there is a growing imperative to address the ergonomic challenges associated with its prolonged use. The need for ergonomic consideration in AR design is crucial to mitigate the risks of postural fatigue and ensure that advancements in AR contribute positively to user well-being. Our analysis of motion capture data has provided pivotal insights, affirming the connection between escalating physical demand and changes in body posture.

5.1 Regression Model

Table 2 indicates that modules 5 to 8 were omitted from the regression model, which only comprises modules 1 to 4. Based on the results, the standard deviation values, ranging between 10 and 15, reflect a higher consistency in participant responses, likely driven by the introduction of new and engaging content. This consistency provides a more reliable basis for linear regression analysis. However, in the latter modules (5 to 8), the standard deviation increases between 17 and 20. This change indicates altered participant learning behavior from understanding new learning material to applying previously learned concepts in problem-solving. Additionally, participant fatigue becomes more pronounced in these later modules, especially after extended engagement periods [19]. These factors contribute to larger variability in postural responses, making the data from these modules less suitable for a linear regression model that seeks to capture consistent patterns.

5.2 Relationship Between Slouching Score and NASA TLX PD

The relationship between slouching scores and NASA TLX PD values revealed a proportional link. As users progressed through AR modules, a decrease in slouching scores was associated with an increase in perceived physical demand, according to NASA TLX PD values. This correlation highlights the slouching scores as a viable measure for assessing the ergonomic impact of AR interfaces, emphasizing the importance of considering physical demand in the design and assessment of AR experiences.

The linear regression analysis produced a combination of positive and negative coefficients. Notably, Modules 1 and 3 exhibited negative coefficients, implying that higher average slouching scores, indicative of more relaxed postures, were associated with lower predicted physical demand values. In contrast, Modules 2 and 4, characterized by positive coefficients, suggested an inverse relationship; higher average slouching scores indicated an increase in the predicted physical demand. This pattern is attributed to the content and complexity of these modules: Modules 1 and 3 were less challenging and physically demanding, allowing participants to adopt more relaxed postures and perceive lower physical demands. Conversely, Modules 2 and 4, involving new, complex information and problem statements, required heightened attention from participants. This increased engagement led to less relaxed postures, as detected by our motion capture sensors, and a consequent rise in physical demand.

5.3 Explain the Correlation of Both Predicted and Actual NASA TLX PD

The correlation analysis between predicted and actual NASA TLX PD values demonstrated a significant positive relationship, affirming the predictive strength of our regression model. A strong correlation indicates that the slouching scores are dependable indicators of perceived physical demand in AR environments. This finding supports our decision to focus on the first 4 modules of the lecture for more accurate prediction. Which explains that the hypothesis of fatigue influence in AR environments can be observed and influential.

6 Conclusion

Our study embarked on a significant exploration into the ergonomic implications of Augmented Reality (AR). The findings revealed critical insights into the effects of prolonged AR engagement on user posture and fatigue, highlighting the necessity for ergonomic considerations in AR systems. In our research, we successfully identified delicate physical demand variations in body movement within augmented reality (AR) settings. Our results, especially those related to the 'slouching scores' obtained from motion capture data, showed a clear change in postural stability associated with prolonged exposure to AR.

Our analysis concluded a significant correlation between our slouching scores and the NASA TLX Physical Demand (PD) values, suggesting that as participants reported higher physical demand, their postural stability decreased accordingly. This correlation underpins the importance of detecting user comfort and fatigue in the design of AR systems, especially in educational and training contexts where prolonged use is common. However, our research is not without limitations. The data was drawn from a small sample size, and the study's scope was confined to specific AR modules in an educational setting. Future research should thus aim to expand the sample size and diversify the AR content to further validate and generalize our findings. Also, the integration of machine learning and advanced predictive models stands out as a promising avenue for enhancing real-time analysis and intervention strategies in AR systems. Technologies could enable the development of adaptive AR systems that dynamically adjust content presentation based on real-time assessments of user fatigue and engagement.

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