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RESEARCH ARTICLE

Measuring physical demand in Augmented Reality learning environments

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ABSTRACT

Augmented Reality revolutionises education by enhancing learning with interactive, immersive experiences. However, the impact of long-term AR use, particularly in terms of physical demand, within educational environments remains poorly understood. This study investigates the relationship between AR engagement and physical demand, utilising motion capture technology, NASA Task Load Index, and HoloLens eye-tracking to quantify user posture, engagement, and perceived workload. We hypothesise that prolonged AR interaction results in a change in slouching scores, indicating increased fatigue. The results show a strong correlation between the slouching score and the NASA-TLX physical demand score. Our study lays the groundwork for incorporating predictive modelling to develop proactive physical demand measures.

Practitioner Summary: Measuring physical demand during AR-based learning is possible using the slouching score. This metric enables dynamic assessment of user physical demand in AR environments, paving the way for improved AR system design to minimise physical fatigue during tasks or learning, enhancing overall user comfort and performance.

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Augmented Reality; postural fatigue; physical demand; motion capture

1. Introduction

In the rapidly evolving digital era, Augmented Reality (AR) stands at the forefront of transformative technologies (Rampolla and Kipper 2012), bridging the gap between virtual and physical realms to enhance user experiences across various domains. The beginning of AR technology, dating back to the 1960s, laid the foundation for a future where digital information seamlessly integrates with the physical world. AR has been broadly defined as the enhancement of natural feedback provided to the operator through the integration of simulated cues using see-through or monitor-based displays (Milgram et al. 1995). Over the decades, advancements in computing power, sensor technology, and software development have propelled AR from conceptual prototypes to sophisticated systems capable of enhancing reality with virtual overlays (Rampolla and Kipper 2012).

In educational contexts, AR's potential to augment learning experiences with interactive, three-dimensional content offers a compelling tool for engaging students and enriching curricula. AR offers a range of benefits, from improving students' spatial abilities to facilitating knowledge acquisition and helping them grasp abstract concepts in engineering physics (Czok et al. 2023). Also, AR has been found to boost motivation levels among learners, providing valuable insights for a deeper understanding of the dynamics involved in educational environments (Chen et al. 2024). By integrating interactive virtual 3D models into natural environments, AR offers an engaging learning experience that develops self-regulation skills, which are essential for academic success (Arici 2024). It means that AR's integration into educational settings heralds a new era of immersive learning, offering dynamic, interactive methodologies that promise to redefine traditional pedagogical approaches. However, as AR technologies gain traction in classrooms and learning environments worldwide, there emerges a critical discourse surrounding their implications—specifically, cognitive overload, distractions, technical challenges (Peeters, Habig, and Fechner 2023), and the physical fatigue resulting from prolonged engagement with AR systems (Halim et al. 2012).

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In the realm of AR, where users often engage with digital content through wearable devices or mobile applications for extended periods, there is a growing concern over the fatigue risks associated with such interactions (Halim et al. 2012). These risks, manifesting as postural fatigue, encompass the physical demand or musculoskeletal strain experienced due to prolonged maintenance of certain body positions. Given the immersive nature of AR, users may remain oblivious to the onset of fatigue until physical demand becomes pronounced, potentially impairing learning outcomes. Observations indicate that these effects are manifested in the torso (Granata and Gottipati 2008), highlighting ergonomics assessment. In AR environments, the dynamic interplay between physical and virtual settings necessitates the development of effective strategies to measure physical demand and fatigue, addressing the future challenges of an AR lifestyle. The existing body of literature on AR predominantly concentrates on its technological, instructional, and cognitive aspects, with scant attention to the physical demands it places on users (Garzón, Pavón, and Baldiris 2019). This oversight highlights a critical gap in our understanding of AR's comprehensive impact, underscoring the necessity for a detailed investigation into how AR-induced postural adjustments correlate with physical demand and overall user well-being. Although there are several subjective measurement tools (Gawron 2019) to assess physical demands, they are not designed to effectively capture the dynamic changes in physical demand. To tackle these challenges, it is essential to integrate insights from diverse studies to provide a holistic understanding of the effects of fatigue, the ergonomic implications of technology use (Fiľo and Janoušek 2022), and the role of statistical methodologies in assessing these phenomena (Aukstakalnis 2016; Lutabingwa and Auriacombe 2007).

Recently, the integration of physical exertion with dynamic tasks illuminates the multifaceted nature of fatigue and its effects on both physiological functions and performance (Mizuno et al. 2011), revealing profound implications for biomechanics, injury prevention, and the enhancement of outcomes through physical activity. Pivotal research in the domain of running biomechanics, as elucidated through tri-axial trunk accelerometry (Schütte et al. 2015), highlights a significant increase in variability within horizontal plane trunk accelerations under fatigue, particularly in mediolateral and anteroposterior directions. This variability suggests compensatory kinematic adjustments that potentially elevate the risk of musculoskeletal injuries, emphasising the need for incorporating fatigue considerations into training regimens and rehabilitation protocols to mitigate injury risks and enhance performance sustainability (Halim et al. 2012). Moreover, the interconnectedness of physical exertion and task demand not only impacts physiological functions but also emphasises the potential of leveraging physical activity to enhance outcomes (Marcora, Staiano, and Manning 2009). According to the study done by Evans and Winter (2018), physical fatigue can be measured by analysing the location of the centre of mass (COM).

Hence, our study postulates that prolonged engagement with AR technologies in learning environments precipitates notable changes in user posture—specifically, a shift in the centre of mass (COM)—indicative of escalating fatigue levels. This hypothesis is rooted in the premise that sustained interaction with AR content, requiring users to maintain fixed positions or perform repetitive movements, increases physical demand, manifesting in altered postural dynamics. To explore this hypothesis, the study adopts a multi-disciplinary approach, integrating motion capture technology to accurately capture and analyse postural changes, alongside workload assessment tools such as the NASA Task Load Index (Hart 2006) and HoloLens eye-tracking. These methodologies collectively enable a comprehensive evaluation of the relationship between user posture, engagement, and perceived workload in AR learning settings. To quantitatively measure the shift of COM in AR learning environments, we introduced a new method, termed the 'slouching score', using motion capture technology. We compared the slouching scores with NASA-TLX physical demand scores to validate their relationship.

The findings from our study reveal a discernible decline in slouching scores associated with increased NASA-TLX physical demand scores during AR-based learning. The implications of our findings could extend beyond academic discourse, offering practical insights for developers and practitioners aiming to harness AR's educational potential without compromising user comfort. In synthesising our research outcomes, this paper contributes significantly to the developing discourse on the intersection of technology, ergonomics, and education. By elucidating the challenges posed by AR technologies, our study not only enriches academic literature but also provides a foundational basis for future innovations in AR design.

2. Method

2.1. Experiment setup

The experimental setup (Yu et al. 2023) is designed to assess the efficacy and usability of an innovative educational tool that integrates Augmented Reality (AR),

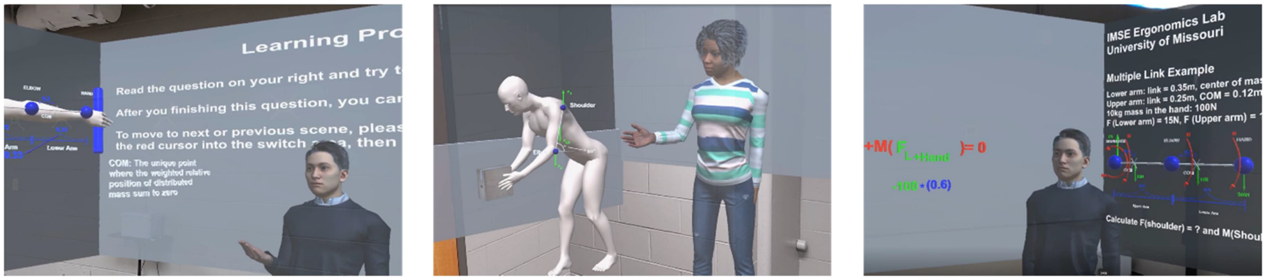


Figure 1. 3D scenes of an AR module built with unity.

Near-Field Electromagnetic Ranging (NFER), and motion capture technologies. This system aims to enhance the learning experience in engineering education, providing a unique and immersive learning environment while also enabling the collection of detailed data on student interaction and engagement.

At the core of the experiment is an AR-based instructional system, developed to deliver two distinct lectures on engineering topics. The system employs Microsoft HoloLens 2 as the AR interface, chosen for its advanced holographic projection capabilities and its ability to create a seamless blend of physical and digital learning environments. The HoloLens 2 is not only a display device but also a data collection tool, capturing eye-tracking data that offers insights into where students focus their attention during the learning process.

The experiment's physical setup is organised within a controlled environment, where participants can navigate and interact with the AR content. The environment is divided into specific zones, each corresponding to different segments of the modules see Figure 1. This spatial division is integral to the experiment, as it allows for the incorporation of the Q-Track NFER system (Schantz 2007), which is used for precise indoor location tracking. The NFER technology allows physical engagement and navigation in the AR environment.

In addition to the location tracking, participants are outfitted with Xsens motion capture sensors (Roetenberg, Luinge, and Slycke 2009). These sensors are placed on various parts of the body to capture detailed movement data, see Figure 2. This motion data is vital for understanding how participants interact with the AR system and for developing future gesture-based controls that can enhance interactivity within the AR learning environment.

The AR content is developed using the Unity game engine, known for its robust capabilities in creating immersive 3D environments. The lectures are designed as a series of interactive 3D scenes, each representing different concepts and elements of the engineering curriculum. Autodesk 3ds Max is used to create complex 3D models and animations, which demonstrate virtual instructors and provide supplementary information displayed in various panels that are then integrated into the Unity scenes, adding depth and realism to the educational content. The lectures are carefully crafted to vary in difficulty - with Lecture 1 consisting of 7 modules, where learning and solving for each module are relatively easier, focusing on basic concepts and definitions (declarative knowledge). Lecture 2 consists of 8 modules, where learning and solving for each module are more challenging, involving complex calculations and problem-solving (procedural knowledge). This variation allows for an assessment of how the difficulty level impacts the usability and effectiveness of the AR system.

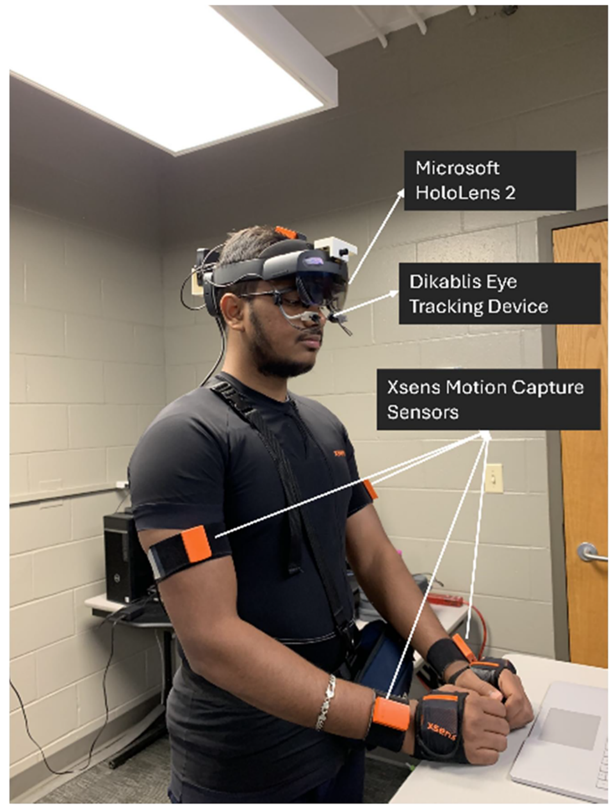


Figure 2. Equipped hardware components.

2.1.1. Content of AR learning modules

Lecture 1 (Duration: 15 minutes for the modules, 25-30 minutes total based on participants' solving capabilities):

- Module 1: Introduction to new concepts in biomechanics.
- Modules 2 & 4: Problem explanation and solving related to forces and momentum on animated objects and achieving static equilibrium.
- Module 3: Further exploration of new concepts on static equilibrium.
- Module 5: Introduction of biomechanical principles as they apply to the human body during object lifting.
- Modules 6 & 7: Detailed problem-solving with calculations on forces and momentum in human body dynamics, supplemented with necessary biomechanical data.

Lecture 2 (Duration: 27 minutes for modules, 40-50 minutes total based on participants' solving capabilities):

- Module 1: Recap of Lecture 1 and introduction to new problems in Lecture 2.
- Modules 2 & 3: Explanation and analysis of a biomechanical problem involving different ways of holding a box.
- Modules 4 to 7: Progressive problem-solving on forces and moments acting on different arm segments, each focusing on a specific part but building upon the last.
- Module 8: Conclusion and comprehensive resolution of the problems discussed.

This research complied with the Code of Ethics and was approved by the Institutional Review Board of The University of Missouri. 21 undergraduate engineering students participated in this experiment. All subjects had their informed consent before they participated in the study. These individuals are selected based on their enrolment in engineering courses that provide them with a foundational knowledge of AR content presented. To ensure participants are well-acquainted with the AR technology and the structure of the experiment, a training session is conducted before the commencement of the experiment. This phase is important for familiarising students with the AR equipment and the overall experimental protocol, setting the stage for their engagement with Lecture 1. The experiment involves participants' interaction with two distinct AR lectures. Lecture 1 this initial lecture series is structured to facilitate ease of learning and solving, ensuring participants can smoothly navigate through the 3D scenes and effectively engage with the foundational material. In contrast, Lecture 2, which participants engage with after a rest period of at least 4 hours but no more than 48 hours following Lecture 1, consists of 8 modules.

As participants navigate through the 3D scenes and interact with the content across both lectures, their engagement is multi-dimensional. Following each lecture segment, participants complete quizzes and assessments tailored to the content they have just encountered. These assessments play a pivotal role in evaluating immediate learning outcomes and the efficacy of the AR system in facilitating knowledge acquisition. By integrating direct assessments of learning outcomes with user feedback, the experiment aims to provide a holistic understanding of the AR system's effectiveness.

Data collection is extensive and multi-layered. The experiment generates a dataset encompassing performance data (quiz scores), usability feedback which includes metacognition awareness, NASA TLX forms, and tracking data (HoloLens eye-tracking, D-lab eye-tracking, and motion data). This data is subjected to rigorous statistical analysis to test the study's hypotheses, evaluate the effectiveness of the AR system, and understand the nuances of how students interact with and learn from this innovative educational tool. This experimental setup represents a comprehensive approach to evaluating an AR-based learning system. It not only assesses the system's effectiveness in delivering educational content but also provides deep insights into the ways students interact with and respond to AR technology in a learning context.

2.2. Data processing

This subsection elaborates on the methodologies utilised for processing and refining the collected data to focus on specific aspects relevant to our study objectives.

2.2.1. Segmentation of data

This step is pivotal in narrowing down the vast dataset to specific, relevant metrics. By concentrating on data related to position and the centre of mass (COM) from the motion capture dataset, you isolate the elements crucial for analysing postural dynamics. This segmentation is not just a data reduction technique; it's a strategic move to zoom in on the most telling indicators of how participants interact with and respond to the AR environment.

2.2.2. Visual analysis for postural dynamics

In this phase, we initially focused on generating visual representations to examine shifts in balance, as indicated by changes in COM (Stapley et al. 1999) and position data. Through these visual interpretations, we gained valuable insights into the participants' postural dynamics during their engagement with the AR environment. The visual tools helped us discern patterns and subtle shifts in the COM, which were not as immediately apparent in the position data. This decision was driven by the realisation that the COM data offered a more direct and quantifiable measure of the participants' postural stability and adjustments, which are critical factors in understanding their physical interaction with the AR system.

2.2.3. Synchronisation of timestamps for Data Alignment

In the study, we employed a meticulous process for aligning the timestamps of two distinct but complementary datasets: the motion capture data and the HoloLens eye-tracking data. This alignment was crucial to segregate the data according to participant activities, particularly differentiating between the learning and problem-solving phases of the modules. The alignment was achieved through a dynamic approach named 'Data Alignment and Frame Indexing'. The HoloLens eye-tracking data consisted of 2 files for each module, with each file representing learning and problem-solving activities. The columns in the HoloLens dataset included timestamps and detailed information about the participant's gaze direction and focal points, such as the following:

- Timestamp: The exact time at which the data was recorded.
- Target data: The name of the panel or object the participant is looking at.
- Gaze Point: The coordinates of where the participant is looking, represented as a 3D point (x, y, z).

For the motion capture data, which followed the Xsens motion capture system, we had a set structure that included the frame number and the Centre of Mass (COM) positions in three-dimensional space. The columns in this dataset were as follows:

- Frame: The specific frame number, corresponding to a particular moment in time (captured at 60fps)
- COM pos X, COM pos Y, COM pos z: The x, y, z coordinates of the participant's centre of mass at that frame respectively.

The process began by gathering the start and end timestamps for each module or scene from the HoloLens data. We then calculated frame numbers at a fixed rate of 60 frames per second, as dictated by the Xsens system, using these timestamps. This calculation allowed us to define distinct ranges of frame numbers corresponding to the respective modules. Essentially, each frame number from the motion capture data was a snapshot in time, which, when aligned with the corresponding snapshot from the HoloLens data, provided a comprehensive picture of how a participant's gaze direction and focal points correlated with their physical movements.

This precise alignment enabled us to isolate motion capture data that corresponded to specific modules, ensuring that our analysis focused on the periods when participants were actively engaged with the lecture content. By correlating frame numbers and COM positions from the motion capture data with the timestamped gaze data from the HoloLens, we gained a nuanced understanding of the participant's interactions with the AR environment, particularly how their visual attention and physical orientation were synchronised during different educational phases.

2.2.4. Data segregation by module

Following the synchronisation of the motion capture and HoloLens eye-tracking data, we proceeded to the phase of Data Segregation by Module. This step was essential for isolating and analysing the data specific to each learning phase within the individual modules. In this process, we assigned acquired frame numbers to the HoloLens eye-tracking data, ensuring that they corresponded precisely with the motion capture data. This allowed us to match every gaze and head movement captured by the HoloLens with the exact physical position and movement of the participant at that moment, as recorded by the motion capture system. The dynamic approach is a process specifically designed to handle the variability in the eye-tracking data points. Given that eye-tracking data can vary significantly in terms of the number and frequency of data points recorded, it was imperative to develop a method that could dynamically assign frame numbers to these data points, ensuring they align perfectly with the corresponding frames in the motion capture data. The outcome of this process was a set of module-specific datasets that seamlessly integrated motion capture data with frame-indexed HoloLens eye-tracking data. Each dataset now represented a complete picture of the participant's interactions within a specific module, capturing both their physical movements and gaze patterns in a synchronised manner. This integrated dataset was then primed for an in-depth analysis.

2.2.5. Data filtering for focused analysis

The initial step in this phase was the addition of a new column in our dataset, which described the direction of the participants' gaze, such as whether they were looking towards the central panel, left panel, or other areas within the AR environment. However, upon further scrutiny of the data, we encountered a significant challenge: there was considerable 'noise' or extraneous data, primarily resulting from the participants' movements as they shifted their gaze across different panels within the 180-degree visual field of the AR setup. Such movements often led to complex and erratic data patterns, making it difficult to isolate key moments of interaction and engagement. To tackle this issue, we implemented a targeted approach to filter the dataset. We narrowed our focus to specifically identify and analyse instances where participants were directly facing the central panel. The rationale behind this decision was twofold. Firstly, by concentrating on moments when participants were looking straight ahead at the central panel, we could significantly reduce the complexity and variability in the data caused by their movements. This reduction in variability was key to achieving cleaner, more reliable data for analysis. Secondly, this focused approach allowed us to better assess instances of postural stability. When participants faced the central panel directly, there was minimal twisting or turning of their COM, leading to more stable and consistent postural data. This refined dataset, now concentrated on moments of direct engagement with the central panel, provided us with a clearer and more accurate representation of participant behaviour and interaction within the AR environment.

2.2.6. Visual representation

We employed visual analytical tools to transform our refined datasets into intuitive graphical representations. This stage was essential in making the complex data more accessible and understandable. We created a variety of graphs and charts that visually narrated the participant's journey through the AR learning environment. These visualisations highlighted key aspects such as the frequency of gaze towards specific panels and changes in posture over time, providing an immediate and clear understanding of participant behaviour and engagement. Once these visual representations were established, we prepared the data for export, formatting it for further detailed analysis and broader presentation.

This approach not only facilitated a smoother transition into the data analysis phase of our study but also ensured that our findings were presented in a clear, concise, and impactful manner. In each of these steps, coding and software tools play a crucial role.

3. Data analysis

3.1. Postural dynamics analysis

Using the filtered motion capture data, we plotted the deviations of the COM positions (x, y, z) from the overall average for each module. The variations in 'COM pos x' occasionally displayed significant differences from the average, indicating lateral shifts in balance that might reflect a response to the AR content. The analysis included a comparison of the deviations in the COM from reference points for each module. The visualisations suggested meaningful insights into postural dynamics, providing significant evidence of the relationship between postural variation and physical demand. The COM deviations indicated that certain modules might place greater physical demands on participants, leading to more noticeable postural adjustments.

3.2. Slouching score analysis

In our research, a significant portion of our data analysis was devoted to the computation and interpretation of slouching scores. This metric was creatively developed to quantitatively assess the postural changes experienced by participants while using AR systems (see Equation 1). In our study, the slouching score acts as a numerical gauge, ranging from 0 to 100, that measures the degree of a participant's postural deviation from a predetermined baseline. A slouching score of 100 signifies no deviation from this baseline posture, whereas lower scores indicate greater deviations. A score of 0 represents the maximum deviation observed, suggesting a significant postural change that may lead to a high physical demand. This scoring system allowed us to precisely measure and analyse the ergonomic impact of prolonged AR use on participants' posture.

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

The calculation of slouching scores was based on establishing a baseline posture. This baseline was determined by analysing the average position of the Centre of Mass (COM) in the x-direction ('COM pos x')

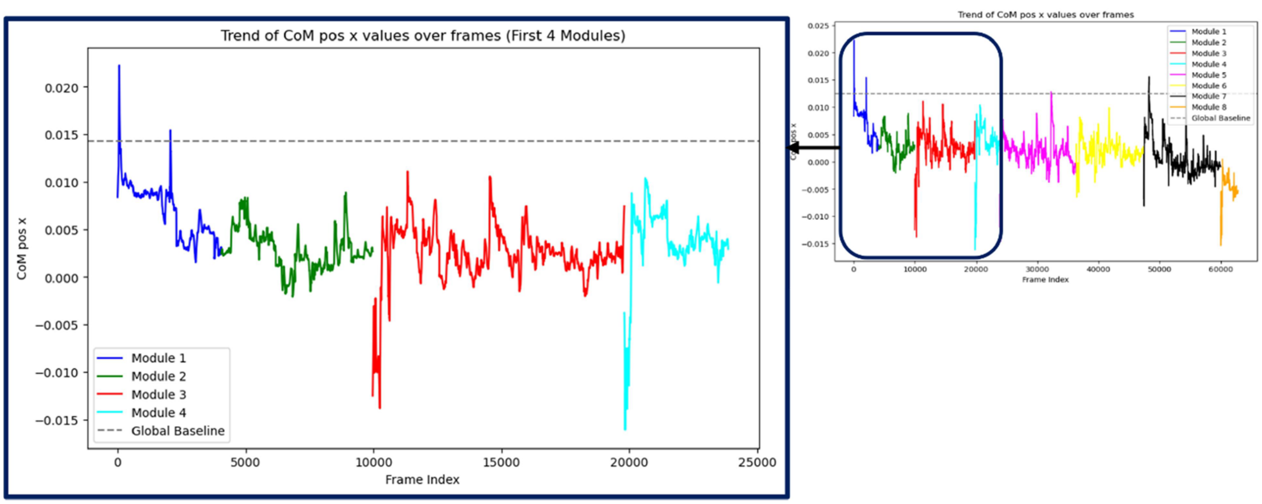


Figure 3. Frame-by-frame COM pos X trajectory across modules.

during the first 4 seconds of data collection before 'Module 1'. We found that participants maintained relatively stable postures during this initial time frame. Following the establishment of this baseline, we moved forward to conduct the evaluation aimed at identifying the maximum deviation from it. The process involved a detailed analysis to identify 240 deviations in the 'COM pos x' for each participant by sorting in ascending order, emphasising the most significant shifts from their baseline posture. The number 240 was chosen to align with the amount of time considered for the baseline, as each second is composed of 60 frames. Thus, 4 seconds equate to 240 frames. The mean of these deviations provided a threshold for what we considered substantial postural change. By focusing on these scores, the analysis could reveal broader patterns and trends that might be obscured in a frame-by-frame examination see Figure 3.

3.2.1. Final steps in slouching score analysis

As the concluding part of our slouching score analysis, we calculated the average slouching scores for each module. This step was important in distilling the vast amount of data into manageable, module-specific insights, reflecting the variation in postural dynamics throughout the different phases of the AR experience.

Upon obtaining these average scores, we prepared to compare them with the NASA-TLX Physical Demand (PD) values. The NASA-TLX PD is a subjective assessment tool designed to evaluate the physical demands and workload. Each aspect of the NASA-TLX, including the Physical Demand subscale, is rated on a scale of 0 to 100. Here, a score of 0 signifies very low demand, while 100 represents extremely high demand. This comparison analyzes the relationship between objective postural data, as indicated by quantified slouching scores, and the subjective experience of NASA-TLX PD. For instance, a high slouching score nearing 100 is usually interpreted to signify a lower rating on physical demand. A higher slouching score represents a smaller posture deviation compared to the baseline posture, suggesting that the participant requires minimal physical effort. It means a low physical demand environment where the participant's body does not experience significant strain. In contrast, a low slouching score indicates a noticeable deviation from this baseline posture. Such deviations could involve hunching, leaning, or other postural changes typically resulting from increased physical effort or discomfort. As a result, participants with lower slouching scores, reflecting these more pronounced postural alterations, would likely report a heightened sense of physical demand associated with their activities. This relationship is further supported by the NASA TLX PD component, which evaluates the perceived level of physical effort required. Therefore, as participants encounter more significant postural changes—evidenced by reduced slouching scores—they may experience an increase in their reported physical demand levels when interacting with the AR system.

This comparative analysis aims to establish how the physical changes in posture, quantified objectively through slouching scores, align with the participants' subjective perceptions of physical demand. The detailed results of this comparison, along with their implications, are extensively discussed in the results section of our research.

3.2.2. Prediction and correlation analysis

In this phase of our research, we concentrated on discerning the impact of average slouching scores, derived module-wise, on the physical demand as perceived by participants. This step involved creating a new dataset exclusively composed of the average slouching scores for each module for 16 participants. Our objective was to utilise this dataset to establish a robust linear regression model, thereby unravelling the relationship between slouching scores and the physical demand reported by participants.

3.2.3. Development of the linear regression model

Using the JMP analysis tool, a linear regression model was constructed. The choice of JMP was driven by its advanced statistical capabilities and its proficiency in handling complex datasets. The model was structured as follows (Equation 2):

$$Predicted\,PD = Intercept + \beta_1(\text{Module1}) + \beta_2(\text{Module2}) + \ldots + \beta_n(\text{Modulen}) \tag{2}$$

The primary goal of this model was to quantify the influence of each module's slouching score on the perceived physical demand (NASA TLX PD). The variables β1, β2, …, βn represent the estimated coefficients for each module, essentially capturing the unique impact of each module on the physical demand. The Intercept in the regression equation is a constant that provides the baseline level of perceived physical demand, independent of the slouching scores.

3.2.4. Significance of the regression coefficients

Each coefficient (β1, β2, …, βn) in the regression model serves as a crucial indicator. A positive coefficient suggests that an increase in the slouching score for that module is associated with an increase in the perceived physical demand, while a negative coefficient indicates the opposite. These coefficients, therefore, provide a nuanced understanding of the relationship between postural dynamics in each AR module.

3.2.5. Correlation

Beyond developing the regression model, we also conducted a correlation analysis to measure the strength of the relationship between the predicted PD values (from the regression model) and the actual NASA TLX PD values reported by participants.

This is performed to solve the following questions.

- Validation of Predictive Model: It helped in validating the relevance of our linear regression model. A strong correlation would indicate that the model is effective in predicting PD based on slouching scores.
- Understanding Subjective Perceptions: By correlating the objective data (slouching scores) with subjective assessments (NASA TLX PD values), we gained insights into how physical changes are perceived and experienced by users.

4. Results

4.1. Slouching score

The examination of slouching scores across both lectures in our study provides a compelling insight into the physical demands placed on participants engaged in augmented reality (AR) learning environments. A consistent pattern emerges from the data: a gradual decline in slouching scores across the initial modules, indicating a notable increase in postural deviations and, by inference, an escalation in physical demand and fatigue experienced by participants see Tables 1 and 2.

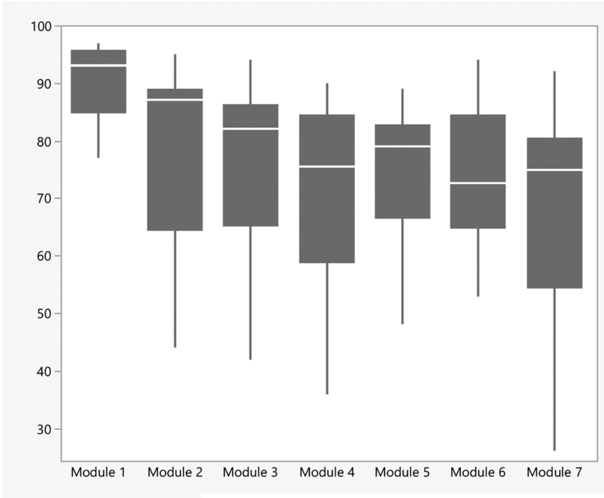
This trend is particularly pronounced in the early modules of each lecture, where the foundational and complex topics are introduced. For instance, a marked reduction in slouching scores from the onset to the completion of these segments signifies an increase in physical demand or adjustment by the participants, mirroring an increase in perceived physical demand, as quantified by the NASA TLX (PD) values.

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

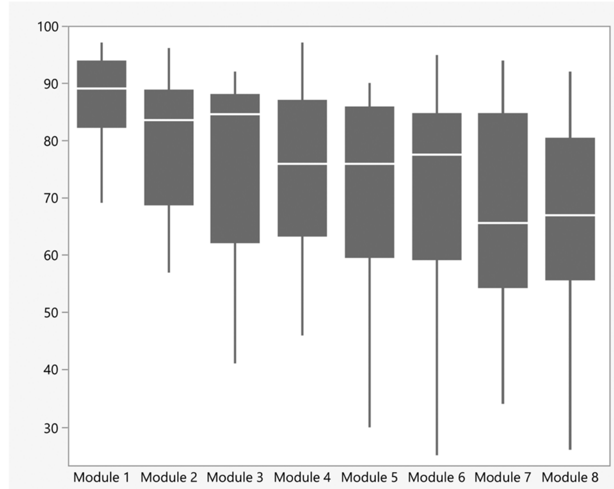
Parameter	Mean	Std Dev	Std Err Mean	Upper 95%	Lower 95%
Module 1	89.31	9.94	2.48	94.61	84.01
Module 2	78.87	16.08	4.05	87.44	70.30
Module 3	75.87	16.29	4.07	84.55	67.19
Module 4	71.85	15.19	3.79	79.97	63.77
Module 5	75.62	10.80	2.70	81.38	69.86
Module 6	74.31	12.26	3.06	80.84	67.77
Module 7	68.31	16.70	4.17	77.21	59.40
NASA TLX PD	25.18	19.75	4.94	35.71	14.66
Predicted PD	21	15.61	3.90	29.32	12.68

Table 2. Average slouching scores of Lecture 2 across modules and NASA TLX PD values of participants.

Parameter	Mean	Std Dev	Std Err Mean	Upper 95%	Lower 95%
Module 1	86.75	9.59	2.39	91.86	81.64
Module 2	80.5	12.01	3.00	86.90	74.10
Module 3	75.12	16.34	4.08	83.83	66.42
Module 4	73.87	14.80	3.70	81.76	65.99
Module 5	72.06	17.74	4.43	81.52	62.61
Module 6	70.12	19.45	4.83	80.48	59.76
Module 7	66.00	18.73	4.68	75.97	56.02
Module 8	66.06	19.62	4.91	76.52	55.60
NASA TLX PD	36.68	27.07	6.76	51.11	22.26
Predicted PD	30.87	18.56	4.64	40.76	20.98



(a) Lecture 1



(b) Lecture 2

Figure 4. Box plot illustrating average slouching scores.

The alignment of slouching score trends with the hypothesised model across most participants underscores a strong correlation between the physical demands of engaging with AR content and the physiological responses elicited. The initial modules, demanding high engagement across multiple panels, present a contrast to later modules where cumulative fatigue might dampen the physical response.

The candlestick plots in Figure 4 display a trend of decreasing average slouching scores across modules in two lectures.

The examination of slouching scores across both lectures in our study provides a compelling insight into the physical demands placed on participants engaged in augmented reality (AR) learning environments. A consistent pattern emerges from the data: a gradual decline in slouching scores, indicating a notable increase in postural deviations and, by inference, an escalation in physical demand and fatigue experienced by participants. The reduction in slouching scores across successive modules in both lectures aligns with our hypothesis that prolonged engagement with AR technology results in increased fatigue, as evidenced by changes in posture.

4.2. Regression model

The best-fit regression model provided a framework for predicting Physical Demand (PD) values for each participant by analysing their slouching scores as they interacted with AR modules. This method involved gathering and evaluating slouching data collected during participants' interaction with the AR experiences. By comparing the actual PD values measured using the NASA TLX and the predicted PD values obtained from our regression analysis, we can highlight the accuracy of predictions and provide insights into the connection between slouching scores and perceived physical demand in an AR environment.

Table 3. Regression coefficients for slouching scores of Lecture 1 by AR modules.

Slouching scores	Regression Coefficients	Std Error	t Ratio	Prob>|t|
Intercept	69.76158	40.81793	1.71	0.1155
Module 1	0.35709	0.58694	0.61	0.5553
Module 2	−0.06574	0.45306	−0.15	0.8872
Module 3	−1.00859	0.32904	−3.07	**0.0108**
Module 4	0.07297	0.40764	0.18	0.8612

The first set of regression coefficients, associated with Lecture 1 in Table 3, indicates that the modules had varied impacts on the participants' centre of mass (COM) deviation, with Module 3 showing a significant negative effect, implying that it led to more pronounced postural deviation indicative of fatigue. The other modules did not show significant effects.

In contrast, the second set, linked to Lecture 2 in Table 4, highlights the relationship between slouching scores and physical demand across different AR modules. Here, both negative (Modules 1 and 3) and positive (Modules 2 and 4) coefficients were observed, suggesting that some modules led to increased physical demand and postural deviation, while others possibly promoted more stable postures or less deviation. The significant coefficients across different modules in Lecture 2 suggest a clearer correlation between the module content or delivery and the physical demand on participants, contrasting with the more mixed or inconclusive findings from Lecture 1.

The scatter plots illustrate the correlation between actual and predicted NASA TLX Physical Demand (PD) scores from a regression analysis. In both plots, individual data points represent paired actual and predicted PD scores for participants. According to Figure 5, the Lecture 1 plot has an R-squared value of 0.59, indicating that around 59% of the variability in actual PD scores is accounted for by the predictions. The associated P-value of 0.0322 suggests the model's predictions are statistically significant. The right plot shows an R-squared value of 0.64, similarly indicating that the model explains 64% of the variability in actual scores. Its P-value of 0.0166 further confirms the model's strong predictive significance.

To support this analysis, we did a correlation analysis between NASA TLX PD values and the Predicted PD values. The result shows 0.8114 for lecture 2 and 0.7668 for lecture 1, which is a high correlation (see Tables 5 and 6).

5. Discussion

5.1. Relationship between slouching score and NASA TLX PD

The analysis provided compelling insights into the relationship between user engagement in AR modules and their physical postures during these activities. Specifically, it was observed that as participants progressed through the AR learning, there was a meaningful correlation between their slouching scores—indicative of their body posture—and their perceived physical demand, quantified using NASA TLX PD values. This relationship supports the idea that slouching scores can serve as an effective and meaningful metric for assessing the physical demands placed on users during AR interactions. The linear regression analysis produced a combination of positive and negative coefficients,

Table 4. Regression coefficients for slouching scores of Lecture 2 by AR modules.

Slouching scores	Regression Coefficients	Std Error	t Ratio	Prob>|t|
Intercept	−22.70897	50.14632	−0.45	0.6595
Module 1	−2.03492	0.75230	−2.70	**0.0205**
Module 2	4.36161	1.01810	4.28	**0.0013**
Module 3	−2.88397	0.77967	−3.70	**0.0035**
Module 4	1.37360	0.50274	2.73	**0.0195**

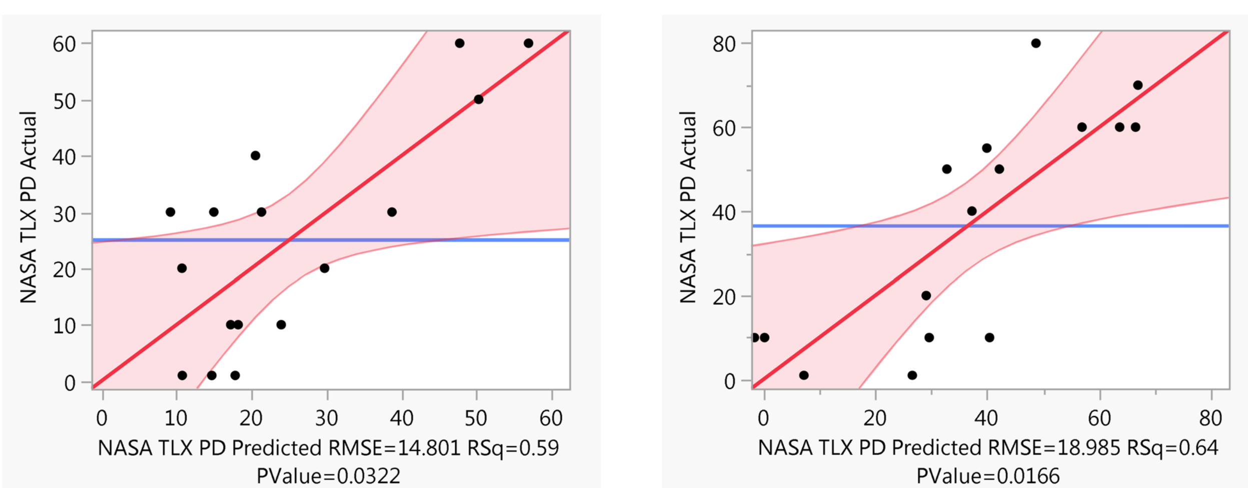
5.2. Explain the correlation of both predicted and actual NASA TLX PD

The correlation analysis conducted to compare the predicted physical demand values with the actual observed NASA TLX PD values revealed a significant positive relationship. This finding demonstrates significant predictive abilities, suggesting it captures the details of physical demands encountered by individuals in AR environments. A substantial correlation between slouching scores and perceived physical demand indicates that the slouching score could effectively serve as an early sign of users' experience with physical fatigue in AR learning environments. This finding supports our decision to focus on the first four modules of the lecture for more accurate prediction. This explains that the hypothesis of fatigue influence in AR environments can be observed and influential (Guo and Kim 2020).

5.3. Interpretation of linear regression coefficients

5.3.1. Lecture 1

Module 3 of Lecture 1, which focuses on the 'Explanation of Static Equilibrium', presents a significant increase in



(a) Lecture 1 (b) Lecture 2

Figure 5. Scatter plots comparing actual NASA TLX PD values against predicted PD values.

Table 5. Correlation matrix of actual vs. predicted Nasa TLX PD scores of lecture 1.

	NASA TLX PD	Predicted PD
NASA TLX PD	1.0000	0.7668
Predicted PD	0.7668	1.0000

Table 6. Correlation matrix of actual vs. predicted Nasa TLX PD scores of lecture 2.

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

physical demand, as evidenced by its negative regression coefficient and significant p-value = 0.0108. This module's complexity, both in terms of conceptual depth and the spread of content across multiple panels likely necessitates extensive learning and physical interaction. Participants are required to engage with multiple panels to grasp the principles of static equilibrium, leading to increased physical movements and adjustments. This broader engagement not only enhances learning but also potentially contributes to higher physical demand, as participants must navigate through the AR environment's spatial layout to connect theoretical concepts with visual representations.

5.3.2. Lecture 2

Modules 1 and 3 are defined by their comprehensive understanding of Lecture 1 content, placing substantial demands on participants. Module 1, serving as a bridge between foundational knowledge and new concepts introduced in Lecture 2, requires significant effort as learners must recall, synthesise, and integrate various pieces of information. The requirement for participants to engage with content spread across multiple panels likely leads them to adopt more static postures. Likewise, module 3 extensively explores problem-solving, demanding that learners fully immerse themselves in the AR environment. This involves applying intricate biomechanical principles to a range of scenarios. It requires the participants to engage with the AR content longer than the modules in Lecture 1, with focused interaction that further contributes to physical demand.

Findings from modules 2 and 4 suggest a contrasting engagement pattern. These modules introduce practical, application-oriented tasks that, while still demanding, are likely to distribute the workload more evenly through dynamic interaction with the AR system. Balancing procedural knowledge and physical activity can result in more varied postures and movements, reducing the probability of physical demand from prolonged static positions. Module 2, for example, involves analysing different postures for holding a box, a task that encourages participants to physically mimic or visualise the actions. In the same line, module 4 emphasises the calculation of forces and moments acting on different body segments, maintaining the trend of active learning.

5.4. The first four modules in the regression model in both lectures

The decision to concentrate the regression analysis on the initial four modules of each lecture is underpinned by several key factors that relate to the participant's interaction with the AR learning environment. These early modules represent a critical phase where participants are introduced to new concepts, leading to heightened declarative/procedural knowledge, and physical engagement. This phase is characterised by a steep learning curve, where the novelty of both the AR platform and the educational content likely elicits more pronounced postural adjustments, captured effectively by slouching scores. As participants progress through the lecture, factors such as physical fatigue, familiarisation with the AR interface, and the diminishing novelty of interaction could lessen the slouching score impact of later modules, making their effects less detectable in the regression analysis. Consequently, focusing on the first four modules provides a more controlled environment to observe and analyse the direct impact of AR educational content on physical demand.

6. Conclusion

Our exploration has revealed insightful findings on measuring physical demand in AR Learning Environments. Using advanced motion capture technology alongside workload assessments, we accurately tracked how users' posture and perceived workload evolved during their interactions with the AR system.

The concept of 'slouching scores', derived from the motion capture data, served as a quantitative measure of postural deviations—a decline in these scores indicated an increase in physical demand. Consistently, across both lecture series, we observed a decline in slouching scores. This trend suggests that as participants explored deeper into the AR content, their engagement led to more significant postural adjustments and, consequently, increased physical demand. Our regression analysis, which focused on the impact of the initial four modules of each lecture, further solidified the link between AR engagement and physical demand. The analysis revealed a clear correlation between decreased slouching scores and increased physical demand, as perceived by participants. This correlation highlights the need for AR systems to be designed with user comfort and physical health in mind. It suggests that while AR has the potential to transform educational experiences by making learning more interactive and immersive, it also poses challenges that must be addressed to ensure the technology supports users' physical well-being.

Despite the compelling insights gained, our study acknowledges certain limitations, such as the small sample size and the concentration on specific AR modules. To build on our findings and enhance their applicability, future research should aim to include a broader participant base and explore a wider variety of AR content. Moreover, there is significant potential for integrating machine learning and predictive modelling techniques into AR systems. As AR technologies continue to evolve and find their place in educational settings, their AR design and implementation must consider not only the cognitive and instructional benefits but also the physical impacts on users. By prioritising ergonomic design principles and exploring advanced predictive technologies, we can ensure that AR systems not only enrich learning experiences but also promote the comfort of users.

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