ATHLONE INSTITUTE OF TECHNOLOGY

A Quality of Experience Evaluation of Augmented Reality and Haptic Feedback in a low-cost Gait Analysis System

DISSERTATION

submitted for the fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

by

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Submitted to Athlone Institute of Technology
June 2020

Declaration

I certify that this PhD dissertation which I now submit for examination, is entirely my own work and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the test of my work. The dissertation was prepared according to the regulations for postgraduate study of the Athlone Institute of Technology and has not been submitted in whole or part for an award in any other Institute or University.

The work reported on in this dissertation conforms to the principles and requirements of the Institute's guidelines for ethics in research.

Signed: ______________________________ Student No.: A00237481   Date: ________

“They say that the best blaze burns brightest,
when circumstances are at their worst.”
Sofie Hatter – Howl’s Moving Castle

Acknowledgements

I would like to thank everyone who has supported me during these years at Athlone Institute of Technology. I feel grateful to all the support I received from the President's Office, International Office, Research Office, Faculty of Engineering and Informatics and all AIT staff.

I would like to thank my supervisor Dr. Niall Murray. His expertise, advice, patience, and support guided my path to become an independent researcher. It was a long journey and I undoubtedly thank him for all the help not only from the research perspective, but also on daily situations, personal problems, and sharing experiences. It was a pleasure to be his student and I wish him all the best in his research career.

I would like to also thank Dr. Ciarán Ó Catháin, who actively acted as co-supervisor. His expertise in sport science, biomechanics, and rehabilitation were crucial in this multidisciplinary research. I would like to also thank Dr. Noel O'Connor, who has also acted as co-supervisor after being the external examiner for my transfer viva. I also thank Dr. Troy McDaniel and Dr. Cristina Muntean, the external examiners for the PhD viva. Their knowledge and review contributed greatly to this final version of the thesis. I also thank Dr. Mark Daly who was the chair for the viva.

I also thank my fellow friends and colleagues from AIT: Guilherme Gomes, Adrielle Nazar, Eoghan Hynes, Emer Coughlan, Katja Osterwald, Ashima Chawla, Romina Pezzoli, and Ana Caroline. Many thanks to Debora Salgado, who has a good friend who always encouraged me. I am particularly grateful to Conor Keighrey (doctor now as well) for many things. I cannot deny the amount of support, funny moments travelling to conferences, going out, sharing experiences, challenges, and accomplishments in the last year. I wish him the best of success in his career and life and hope we can continue making good memories.

I would like to also thank the Government of Ireland and the Irish Research Council for the funding support during my PhD. I extend this to Dr. King Hay Yang and Dr. Peter Tonellato who supported my successful IRC application. In addition, I would like to thank Karl Turley and Mary Simpson from AIT's International Office for all the support they have given me during these years.

Finally, I would like to thank my parents Gilson Rodrigues, Valeria Braga, and Orlindo Guimaraes for their support. They all helped me during some difficult times and shared the joy of each of my achievements during my PhD. I would also thank my friends from Brazil: Thais Berbe, Elenir Maciel, Matheus Coelho, Ludmila Vieira, Wallace, Leo Rander, Hudson, Taisa Higino, Ana Catarina, and all the guys from “Nona”. Thank you!

Abstract

Gait analysis is a technique that is used to understand movement patterns and, in some cases, to inform the development of rehabilitation protocols. Traditional rehabilitation approaches have relied on expert guided feedback in clinical settings. Such efforts require the presence of an expert to guide the re-training (to evaluate performance and provide feedback), the user to attend a clinic and is based on subjectivity of the clinician. Nowadays, potential opportunities exist to employ the use of digitized "feedback" modalities to help a user to "understand" improved gait technique. This is important as clear and concise feedback can enhance the quality of rehabilitation, recovery, and prevent injury. A critical requirement emerges to consider the quality of feedback from the user perspective i.e. how they process, understand and react to the feedback.

In this context, this PhD thesis reports on the design, development, and evaluation of a gait feedback system with two feedback modalities: haptic and augmented reality (AR). The initial part of this PhD work focused on evaluating different motion capture systems as part of an overall gait analysis system. The objective was to develop an alternative, cheaper and more accessible system. The proposed gait system (which included integrated camera and inertial sensors) was compared with the gold standard in motion capture. This was important to determine the most accurate capturing system to use in a feedback application.

The next and major contributions of the PhD project focused on the design of a gait feedback system and evaluating the user Quality of Experience (QoE) of the two gait feedback modalities for knee alignment. The aim of the feedback is to reduce knee varus and valgus misalignments, which can cause serious orthopaedics problems. The QoE analysis aimed to understand how users perceived the proposed Haptic & AR systems in terms of utility, usability, interaction, and immersion. This involved assessing the easiness to adjust to feedback (utility), how easy the feedback was to understand (usability), how users interact with the feedback (interaction), and the awareness of body while moving (immersion). This analysis considered objective (improvement in knee alignment), subjective (questionnaire responses) user metrics, and implicit user metrics (e.g. physiological responses such as heart rate, electrodermal activity and eye information) from users. The findings show statistically significant higher QoE ratings for AR feedback. AR feedback also significantly reduces the number of varus

misalignment (by 31%) when compared to baseline readings. Gender analysis showed significant differences in performance for the number of misalignments and time to correct valgus misalignment for AR feedback for males. The male AR group, the level of reduction for varus was 45% and 18% for valgus misalignments ($p<0.05$). Consistent with the male group, although to a lesser extent, AR feedback reduced the number of varus misalignments by 35% for the female subgroup (not significant when compared to the baseline).

Physiological responses of participants to feedback stimuli are also presented. Event-based comparisons of heart rate showed higher variability for participants during haptic feedback, which could be an indicator of stress and was also reported in the male subgroup. The haptic and AR groups also showed significant differences in electrodermal activity (EDA) for varus, partial alignment (only one leg aligned) and complete aligned (both legs aligned), which could also indicate increased task demand. EDA signals were also filtered through frequency analysis. Pupil analysis reported that when a participant receives AR or haptic feedback and both legs were misaligned (varus or valgus), the pupil diameter was significantly greater for the haptic group, which could indicate an increased task demand. The final analysis dealt with bivariate correlations of physiological measures to check whether involuntary responses after feedback can be correlated and linked to stressful situations. The analysis reported that physiological measures of pupil, skin conductance, and heart rate are correlated to some extent.

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1 Introduction

This chapter outlines the project scope and introduces the research question, key contributions and publications achieved during this PhD work.

1.1 Introduction

The study of human motion is important as it deals with many application areas such as military, sports, medical, robotics, cinema, game creation, and evaluating performance [1]. The study of gait is also an important part of human motion. By definition, gait is a repetitive sequence of movements of lower limbs that moves the body forward, while simultaneously maintaining stability of the body [2]. During gait, one limb acts as a movable support, in contact with the ground, while the contralateral limb advances in the air. It is a cyclic movement as limbs invert their roles with each successive step [3]. In general, gait analysis involves the measurement, processing, and systematic interpretation of biomechanical parameters that characterize human movement. Through gait analysis, it is possible to identify limitations in movement and provide information to guide rehabilitation procedures for orthopaedic issues such as knee varus and valgus misalignments. It also includes prehabilitation for injury and re-injury prevention.

The assessment of human gait facilitates identification of movement deficiencies and abnormalities that are associated with the development of chronic injuries and diseases [4]. From a research perspective, it can also enhance many existing rehabilitation protocols, help with prevention of diseases, and monitor patients pre and post surgeries. Knee valgus and varus are factors that can lead the development of such diseases and are the use case selected for this feedback evaluation. Gait assessment also provides objective data to support gait re-retraining. Gait can be analysed and assessed using a variety of methods such as: clinical evaluation techniques; the use of high-speed cameras; force plates; and inertial sensors [5].

Despite novel methods and technologies to evaluate and improve gait as stated above, there is a lack of research on novel “feedback” methods that can be combined with gait systems to correct or adapt to a gait abnormality. It is known that feedback is a powerful tool for motor skill learning and it helps with sensory perceptual information as part of performing and learning a skill [6]. The accuracy of exercise performance with feedback in physiotherapy influences the healing process of the patient greatly [7]. For rehabilitation to be successful, it is crucial that the patient can understand the feedback provided, either from a clinician or a system. Many rehabilitation and retraining systems use feedback as an important tool for patient learning and to evaluate progress [8]. Some of the feedback modalities in training systems include: 2D screens; haptic; audio; expert guidance; and in more recent times Virtual Reality (VR) and Augmented Reality (AR) [9-11]. AR is an interactive experience in a real-world environment whereby real world objects are augmented with virtual information [12]. The use of AR via wearable smart glasses in the field of gait rehabilitation is an area under researched to-date. AR gives freedom of movement to the user, which can greatly enhance the quality of feedback in rehabilitation. It is also a promising as it can be a light weight, portable and visual feedback.

This work has focused, as the primary aim, on understanding a user`s perceptual quality of haptic and AR based gait feedback within a holistic gait analysis system. However, measuring the user perceptual quality of multimedia experiences is a complex and challenging task, which can be evaluated using qualitative methodologies such as QoE. Quality of Experience (QoE) is a user centric paradigm that allows us to evaluate the “degree of enjoyment or annoyance of an application, system, or service” of a multimedia experience [13]. It represents “the fulfilment of user’s expectation in respect to utility and enjoyment of that application or service” [14]. QoE studies consider numerous factors at various levels such as at human (e.g. gender, age), context (e.g. gait misalignments), and system levels (e.g. comparison of different feedback methodologies). As such, QoE is an appropriate framework to employ to answer the proposed questions outlined in this research.

In the context of the work presented here, the utility (i.e. if a system is useful in satisfying a user’s needs) and usability (i.e. easiness of using a system) of the feedback are the key concerns. In the recent years, with the advent of internet, advanced sensors, and internet of things (IoT), new proposals on evaluating QoE in a continuous manner have been proposed [15, 16], and models of assessing several multimedia systems were built [17]. As such, the proposed work presents a novel and rigorous QoE evaluation of two feedback modalities (AR vs Haptic) within a low-cost gait analysis system. These comparisons are at human (gender analysis), system (AR vs haptic feedback), and context (gait feedback for knee valgus and varus) levels. This evaluation includes data analysis from post-test self-reported measures (explicit), objective data comparison in terms of user responses (i.e. changes in gait if any) to each of the feedback modalities and physiological (implicit) measures of user's QoE. In the next section, the research questions and key contributions of this work are presented.

1.2 Project Proposal and Research Question

As outlined, the primary aim of this PhD is with respect to understanding user`s perceptual quality of haptic and AR based gait feedback within a holistic gait analysis system. This QoE comparison has been undertaken at several levels: human (gender analysis), system (AR vs haptic feedback), context (knee valgus and varus, angles) levels. It employs at system level, the development of a low-cost gait analysis system that can provide quantitative gait variables such as angles and feedback to users. It also includes the user's acceptability through a QoE evaluation and assessment of physiological responses of heart rate, skin conductance, and pupil of each feedback modality.

The research question for this PhD work is:

"What type of feedback, considering haptic and AR, supports the highest QoE in a low-cost gait analysis system?"

To address this research question, several research sub-questions are defined for this project:

- SubRQ1: *Can we objectively and accurately evaluate gait performance in a low-cost gait analysis system?*
- SubRQ2: *What do users self-report when experiencing different feedback systems in terms of key aspects such as experience and effort?*
- SubRQ3: *Can physiological measurements support a better understanding of user's response in the context of a QoE evaluation in a gait feedback system?*
- SubRQ4: *What type of feedback is easier to understand during gait? Haptic or AR feedback?*

- SubRQ5: *Does gender influence user's QoE in a gait feedback system?*

1.3 Contributions

The main contribution of this PhD work is the development and QoE evaluation of a gait feedback system. The following are the contributions of this PhD work:

(I) To design, build and evaluate a low-cost motion capture system for user centred multimodal gait assessment. This research involved comparing marker-less motion capture systems (e.g. Multiple Microsoft Kinects) and Inertial sensors (Shimmer and X-Sens IMUs) with the gold standard VICON system.

(II) To design and develop feedback modules and integrate these with the motion capture system using the optimum devices outlined in (I). This research and development resulted in the gait analysis and feedback system.

(III) To compare different feedback modalities for the gait feedback system considering objective variables of gait (e.g. knee alignment) and QoE subjective (explicit) evaluation (MOS questionnaires, NASA TLX, emotion rates).

(IV) To assess the physiological response to different types of feedback considering physiological responses (implicit measures) of heart, skin and eye responses. It also considers bivariate correlations (if any).

In order to answer the research questions defined and achieve the contributions outlined, the following were the research objectives of this PhD work:

- Research and critique existing technology in gait analysis focused on wearable and camera-based systems. This included performing a state-of-the-art review on gait analysis across related domains (e.g. hip and knee replacement, varus and valgus knee).
- Evaluate if effective gait analysis can be achieved by the integration of wearable devices and marker-less motion capture and determine the accuracy of this system in comparison to a gold standard system.
- Perform a state-of the-art review of QoE evaluations in the key areas related to the scope of this PhD work: feedback modalities (e.g. audio, visual, VR, AR, expert

guidance, etc), rehabilitation, and gait analysis. Research and apply different feedback approaches in a multimodal gait analysis system.

- Develop a low-cost motion capture system by the integration of camera systems and inertial measure units.
- Develop a wireless real-time streaming protocol and gait analysis system considering inertial measure units.
- Develop haptic and augmented reality modules that uses socket connections to the main gait system.
- Experimentally verify how each of each feedback module influence user's QoE in gait evaluation.
- Research and critique research on user QoE in terms of feedback, subjective evaluation, and physiological signals.
- Experimentally, capture and analyse how users self-report their perception of different feedback stimuli (haptic and AR) using post-test QoE questionnaires (e.g. system questionnaires, SAM emotion scale, NASA-TLX.)
- Evaluate the acceptability of wearable feedback devices from the QoE user perspective i.e. evaluate acceptability and utility of feedback system.
- Experimentally, evaluate how physiological measures, workload and emotion affects QoE in a gait feedback.

1.4 List of Publications

Published:

Thiago Braga Rodrigues, Ciarán Ó Catháin, Noel E O'Connor, and Niall Murray. *A Quality of Experience Assessment of Haptic and Augmented Reality Feedback Modalities in a Gait Analysis System*. PLoS ONE (2020), 15(3), e0230570. DOI:https://doi.org/10.1371/journal.pone.0230570

Thiago Braga Rodrigues, Debora Pereira Salgado, Ciarán Ó Catháin, Noel E O'Connor, and Niall Murray. *Human gait assessment using a 3D marker-less multimodal motion capture system*. Multimedia Tools and Applications (2019), 79(3), 2629-2651. DOI:https://doi.org/10.1007/s11042-019-08275-9

Thiago Braga Rodrigues, Ciarán Ó Catháin, Declan Devine, Kieran Moran, Noel E O'Connor, and Niall Murray. *An evaluation of a 3D multimodal marker-less motion analysis system*. In Proceedings of the 10th ACM Multimedia Systems Conference (MMSys '19) (2019). Association for Computing Machinery, New York, NY, USA, 213–221. DOI:https://doi.org/10.1145/3304109.3306236

In addition to the above listed papers that were a core reflection of the PhD work, the following list includes other academic outputs which were contributed to during my PhD study:

Debora Pereira Salgado, **Thiago Braga Rodrigues**, Felipe R. Martins, Eduardo L.M. Naves, Ronan Flynn, Niall Murray, *The Effect of Cybersickness of an Immersive Wheelchair Simulator,* Procedia Computer Science. (160), (2019), 665-670, ISSN 1877-0509, DOI:https://doi.org/10.1016/j.procs.2019.11.030.

Thiago Braga Rodrigues, Debora Pereira Salgado, Mauricio C. Cordeiro, Katja M. Osterwald, Teodiano F.B. Filho, Vicente F. de Lucena, Eduardo L.M. Naves, Niall Murray, *Fall Detection System by Machine Learning Framework for Public Health*, Procedia Computer Science, 141, (2018), 358-365, ISSN 1877-0509, DOI:https://doi.org/10.1016/j.procs.2018.10.189.

Debora Pereira Salgado, Felipe Roque Martins, **Thiago Braga Rodrigues**, Conor Keighrey, Ronan Flynn, Eduardo Lázaro Martins Naves, Niall Murray. 2018. *A QoE assessment method based on EDA, heart rate and EEG of a virtual reality assistive technology system*. In Proceedings of the 9th ACM Multimedia Systems Conference (MMSys '18). Association for Computing Machinery, New York, NY, USA, 517–520. DOI:https://doi.org/10.1145/3204949.3208118

In writing:

Thiago Braga Rodrigues, Ciarán Ó Catháin, Noel E O'Connor, and Niall Murray. *A QoE evaluation of haptic and augmented reality feedback in a gait analysis considering physiological and subjective workload assessment*. IEEE Access, (2020).

Thiago Braga Rodrigues, Ciarán Ó Catháin, Noel E O'Connor, and Niall Murray. *Quality of Experience in haptic and AR feedback: Pupillometry and emotion as measures of cognitive efforts in gait*. IEEE Transactions on Multimedia, (2020).

Thiago Braga Rodrigues, Ciarán Ó Catháin, Noel E O'Connor, and Niall Murray. *A QoE model of feedback in gait analysis considering implicit and explicit measures*. IEEE Transactions on Multimedia, (2020).

1.5 Thesis Outline

This PhD thesis is organised in six chapters. This first chapter has introduced the motivation for the research, the problem to be solved, the research questions and the thesis contributions and publications. Chapter two presents related works for the research areas related to the scope of this PhD, namely: gait and Motion Capture, Immersive multimedia such as Virtual Reality (VR), Augmented Reality (AR), and Haptic interfaces, and QoE. The third chapter describes the first case study of this project: An evaluation of 3D multimodal marker-less systems for motion capture and gait analysis. It contains the aims, methodology and two evaluations conducted as part of an overall gait analysis system. This chapter also gives considerations for the second case study of the project and informs the gait system employed. The fourth and fifth chapters focus on a detailed reporting of the QoE evaluation of haptic and AR feedback in gait analysis. It contains aims, methodology, and QoE evaluations of the gait feedback system. This chapter reports results of tests with participants for varus and valgus misalignment, physiological and workload assessment, and emotion responses as measures of cognitive efforts considering questionnaires and pupillary responses. The sixth chapter concludes this PhD thesis, discussing the key findings and highlighting remaining challenges and recommendations for other research and studies.

2 Related Work

This chapter presents and critiques related works in gait feedback, motion capture, immersive multimedia, and quality of experience. Section 2.1 gives an overview of existing research on gait and gait analysis. It also describes the differences within the area of motion capture including the use of marker-less-based systems, inertial measures, and marker-based systems for gait analysis. Section 2.2 discusses the role of feedback and as part of this, including immersive systems. Section 2.3 defines QoE and informed research in the area of user experience. It describes related works in QoE considering different questionnaires, physiological signal analysis, and many other measures of QoE. The aim of this chapter is to give the reader background on these topics as well as literature used to define the final scope of this research.

2.1 Gait and Motion Capture

Human gait is the sequence of movements of the lower limbs that promotes body locomotion and stability during walking [18]. It is difficult, in clinical subjective observation, to analyse gait and identify deviation from normality without using systems capable of analysing and quantifying movement, such as motion capture systems. Such limitations have led physicians, biologists, engineers, and academics to highlight the need for systems that can provide objective data that describe movement, via accurate recording of human movement, or gait analysis [19].

2.1.1 Gait Analysis

Gait analysis is achieved through the measurement, processing and systematic interpretation of biomechanical parameters that characterize human movement [18]. The appropriate identification of gait parameters promotes assessment of movement limitations and aids in the development of appropriate rehabilitation and prehabilitation procedures [20]. Clinical gait analysis implies the ability to acquire and evaluate, in an instrumented way, the kinematic (study of motion), kinetic (study of forces and torques), and myoelectric information (electric properties of muscles) of the movement. It also includes the ability to interpret this information clinically by integrating specialized personnel [21].

Gait laboratories have been set up to offer accurate gait analysis and evaluate the performance and functionality of populations with musculoskeletal disability or dysfunction. These laboratories can develop quantitative methods of measurement and analysis based on scientific and technical knowledge of human movement [20, 21]. For gait analysis, each sequence of movement involves a series of interactions between two segmented lower limbs and body mass. The sequence of these functions performed by a limb is called the gait cycle (Fig. 1). Each cycle is composed of several actions that pass from one phase to another, with overlapping stages, with no specific end point of one stage and the beginning of the other [22].

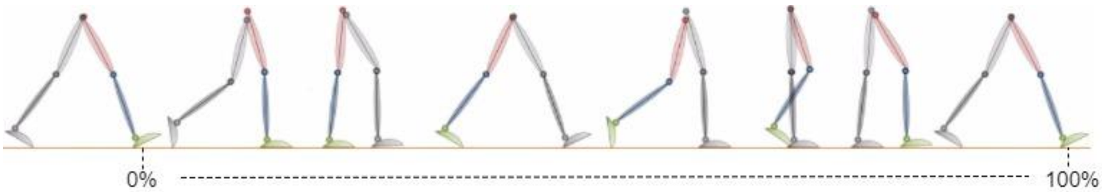

Figure 1. Gait cycle

Understanding the kinematics of the human movement is important to evaluate functional performance of limbs under normal and abnormal conditions. For example: kinematic aspects can support diagnosis and inform intervention plans in the case of an orthopedic surgical intervention, and design of a prosthesis with the purpose of restoring function [19]. Patients suffering from numerous conditions can benefit from instrumented gait analysis, e.g., those with cerebral palsy, traumatic brain injury, neuromuscular diseases, traumatic spinal cord injuries, and those that require congenital amputations of the lower limbs or hip replacement procedures [23, 24]. The instrumented gait analysis can be used to indicate if a movement or force is aberrant, physiotherapy procedures, and adequacy of orthoses and prostheses.

2.1.2 Varus and Valgus Knee

The Hip and knee are weight bearing joints and play a key role in gait stability. The displacement of knee - called varus/valgus - is a misalignment of the tibiofemoral joint. The valgus knee (as per Fig. 2a) is a condition whereby the knees turn outwards, whilst the varus knee (Fig. 2c) is a condition where the knee to turns inwards [25]. This disorder occurs because the tibia is not aligned correctly with the femur, giving a different shape to the leg line. Varus and valgus deformities affects about 70% of people with knee problems in the western population [26, 27]. It is also linked to osteoarthritis which is the most common joint disorder in the world [28].

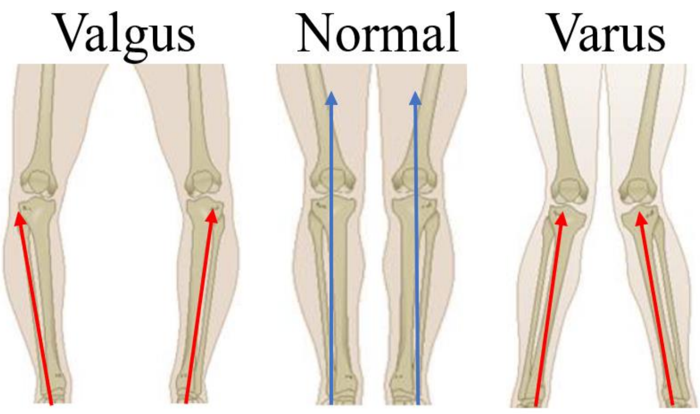

Figure 2. Tibia alignment: Varus (2a), normal (2b), and varus (2c) knee. Red arrows represent misalignment in the tibiofemoral joint. The blue arrows represent alignment of the tibiofemoral joint. Adapted from [29].

Excessive varus/valgus alignment can lead to serious orthopaedics problems such as osteoarthritis [30]. Extreme cases of knee misalignment may need to be addressed surgically. If not properly treated, it can result in severe injuries from joint wear to diseases, e.g. knee arthrosis and osteoarthritis. However, in less severe cases, symptoms can be reduced with physiotherapy, corrective exercises, and through gait re-training [31]. There are some rehabilitation procedures that help reduce varus/valgus knee, such as strengthening of the hip and knee muscles [7]. Rehabilitation or corrective exercises are prescribed and explained by the clinician. Progress on rehabilitation is typically assessed in a subjective manner by a physiotherapist.

2.1.3 Motion Capture

In Biomechanics, Motion Capture (MoCap), is a concept used to describe systems capable of recording body movement through some devices e.g. video cameras and inertial sensors. These systems vary in the number and configuration of cameras, whether or not they use markers, the representation of the captured data, processing algorithms, and application [32]. From this recorded data, kinematic variables of motion are calculated. Such systems allow a quantitative movement evaluation and study of human or animal musculoskeletal system [33]. There are two main types of MoCap technologies: marker-based motion capture and marker-less-based MoCap, defined based on the need (or not) to use reflective markers to detect position. Each type of MoCap technology establishes needs and constraints for the environment in which to capture motion, thus defining the process for the motion capture and the calibration. Moreover, each technology has its pros and cons in gait evaluation [34].

2.1.3.1 **Marker-Based Motion Capture Technologies**

In marker-based MoCap systems, markers are placed at specific anatomical locations. Video cameras with optical electronic devices are used to capture the movements made by the user. The cameras are strategically positioned in space, to allow the tracing of those markers during each trial. Subsequently, the data of these markers are analysed by a computer that tracks each marker position in the three-dimensional space and reconstructs the trajectory of each marker [1].

Marker-based optical systems are expensive and require high-resolution cameras and specialized software for data processing. The benefit of these systems is that they provide excellent accuracy and great detail in the reconstruction of the movements [35]. Some drawbacks include high cost, complex set up and expertise to use them, and the occlusion of markers during the movements. In case of occlusions, further post capture processing to fill the gaps is required. Despite these limitations, marker-based systems are still the most used systems in gait analysis [1, 34]. An example of a marker-bases MoCap system is the VICON system (Fig.3).

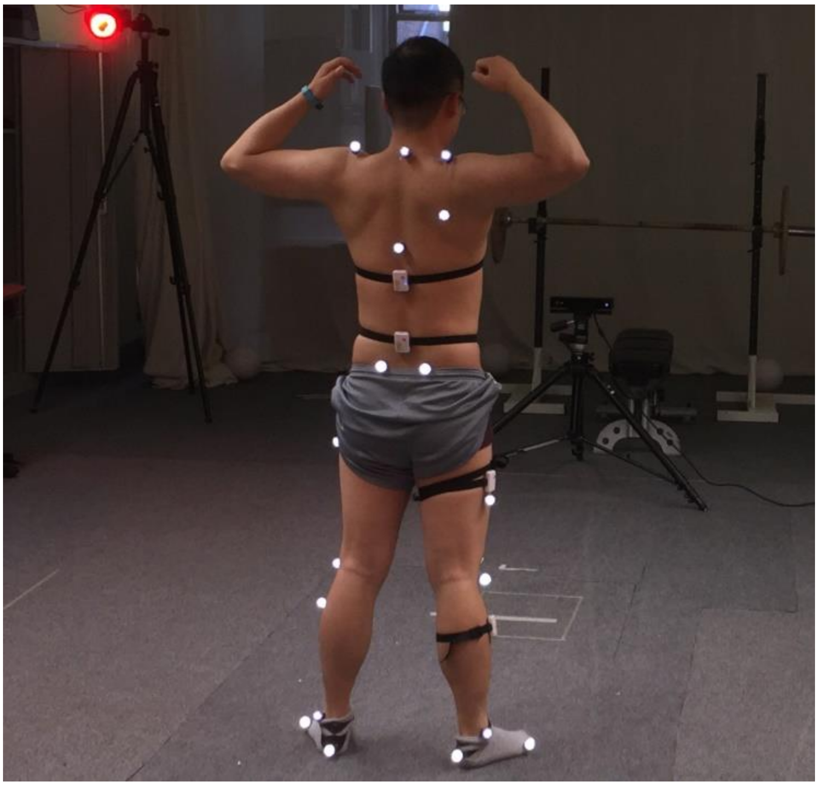

Figure 3. Vicon system and markers

The VICON system offers solutions in three-dimensional motion capture in applications such as gait analysis, postural analysis, motor control, and gait retraining. It can also be used to assess the biomechanics of high performance athletes, as well as other species in the field of veterinary studies with accuracy and high sampling frequency [36]. This system consists of a data station, video cameras and infra-red projectors capable of capturing human movement by the detection of reflective markers placed on a body [37].

In marker-based MoCap, reflective markers should be taped directly onto the skin of the user. In addition to concerns of using adhesive products that are not harmful, the attachment must be sweat resistant and sufficiently adherent so that the participant can move and perform the movement in the most natural way possible. Another important aspect is the difficulty in the repeatability of marker positioning when captures are performed on different days and the need to implement algorithms that address these differences [38].

Whilst known marker-based MoCap systems, such as the VICON system [36] provide highly accurate data, a number of issues exist as mentioned above. As a result, research and industry have also looked at MoCap technologies that do not require the use of reflective markers. Technologies such as the Microsoft Kinect [39] (which uses RGB-D cameras), can capture 3D skeleton data using anatomic landmarks. Such systems potentially provide a better user experience with no movement restriction (truly ecologically valid data) and faster set up [40]. Thus, marker-less tracking technologies like the Kinect are an attractive alternative to marker-based systems.

2.1.3.2 **Marker-less-based Motion Capture Technologies**

Some MoCap technologies do not require the use of reflective markers. Such approaches are less restrictive, thus giving the impression of greater freedom of movement to the user and can overcome the problem of occlusion. The operation of the marker-less MoCap is based on the analysis of the silhouette of the image of the user who is performing the movement in contrast to the background of the image and depth information. The point cloud formed by the silhouette is combined with an articulated model of the human body (Fig.4). The marker-less MoCap technique has been widely used in the creation of devices that efficiently perform the task of translating human motion into a coordinate point that can be mapped by the computer [41].

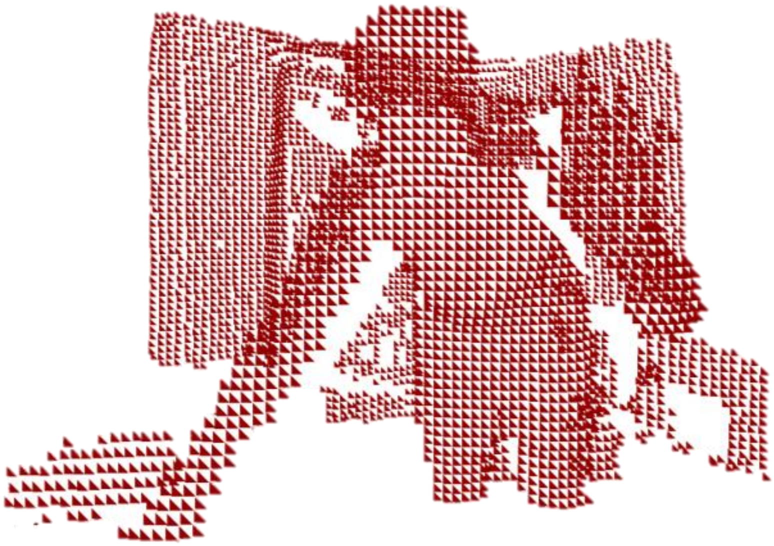

Figure 4. Kinect point cloud from depth sensor.

The depth of a point cloud in the scene is calculated by a Time-of-Flight (ToF) camera from the time the light emitted by the camera travels to the destination and returns to the receiving sensor. These cameras generate images at low resolutions, but at a high frame rate per second [42]. An example of marker-less-based MoCap is the Microsoft Kinect.

2.1.3.3 **Microsoft Kinect**

The Microsoft Kinect (MS Kinect), first introduced in November 2010 (Fig.5), is a motion capture device developed for the Xbox 360 and Xbox One. With the Kinect, Microsoft has created an innovative technology capable of allowing players to interact with electronic games without the need to have a control / joystick. It has brought novel innovative user experience to the gamers and researchers. The device also offers the possibility to monitor, depending on the field of vision, the movement of several people at the same time. The Kinect was discontinued in 2015 and it was replaced by the Azure Kinect, with similar technology for developers. The Azure Kinect has an array of seven microphones and features cameras with wide or narrow angle views for different use cases. It also has a 12MP camera with a color flow that is aligned with the depth system. It is even possible to sync multiple Azure Kinect devices to get different views of the environment. Although Kinect was launched as a gaming peripheral, the accessory immediately stimulated the interest of researchers who were attracted by depth detection and skeleton tracking. Despite the recent development of the Azure Kinect, this work used the MS-Kinect, which was available at the time.

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Figure 5. Microsoft Kinect

The most important functions of MS-Kinect are associated with tracking the user's movements against the interface. For such functionality, hardware components such as an infrared light emitter, multiple video cameras, an infrared camera, a vector of microphones, a three-axis accelerometer and a camera tilt motor are used (Fig.6)

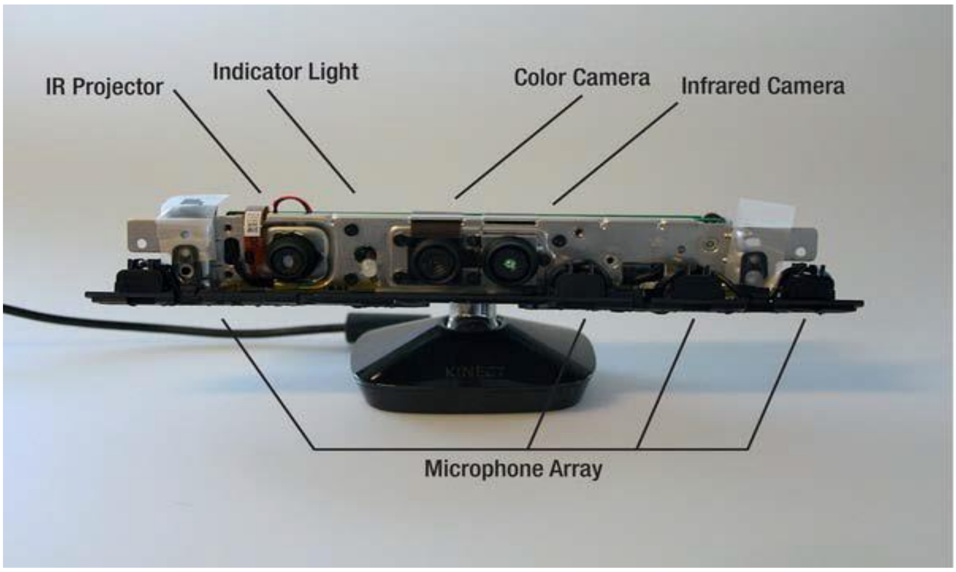


Figure 6. Kinect Components. Available at [43]

MS Kinect can return three-dimensional position of a set of points associated with the main joints of the human body, based on a human reference skeleton [44]. Each skeleton is composed by 25 joint points. The Kinect V2 joint map is shown on Fig.7.

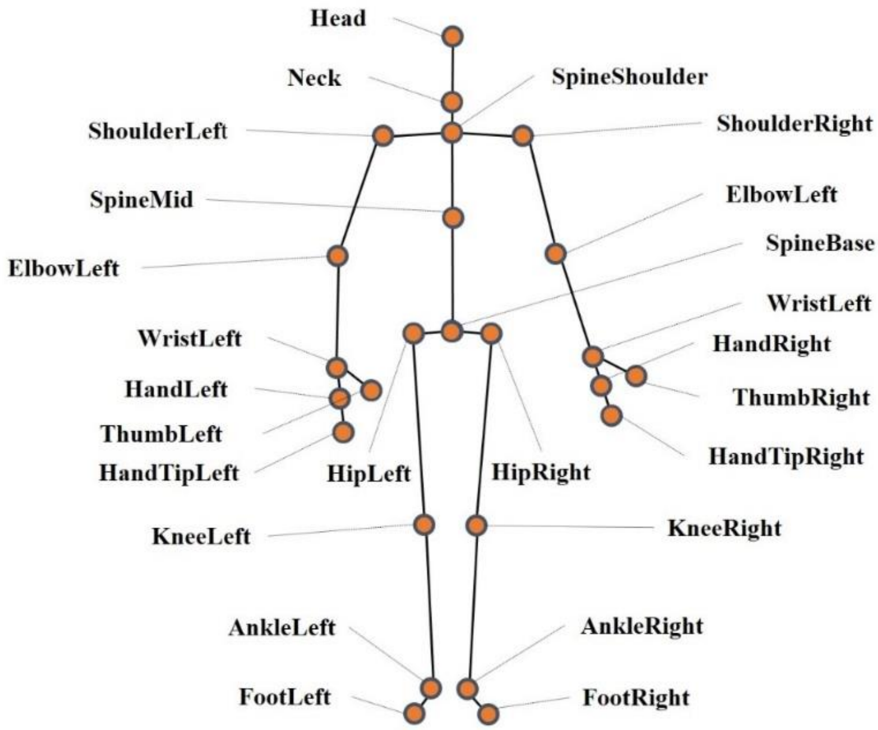


Figure 7. Kinect V2 joint map. Available at [45].

With the MS Kinect, the marker-less MoCap technology demonstrates more accuracy and performance compared with similar technologies [46], allowing this technique to enter not only the realm of entertainment, but also Biomechanics, and specifically gait analysis [47].

2.1.3.4 **Multiple-Kinects**

The skeletal tracking of a single Kinect has some limitations: (i) it was designed to track the users facing the sensor (frontal views); (ii) it cannot discriminate between the frontal and rear views (e.g. even if the user is facing the opposite direction, the sensor still assumes a frontal view); (iii) its tracking frequently fails due to occlusions (e.g. the arms are occluded by other body parts); (iv) Ability to assess/measure/tolerate rotations around the vertical axis is limited; (v) the field of view within which it can track users is quite limited. Crucially, in terms of model accuracy, different joints have variations in accuracies e.g. lower joints are less accurate compared to upper joints [48].

In order to have a 360^{o} of tracking area, increasing the field of view and increasing precision in skeleton detection, multiples Kinects can be employed for a wider detection range. Figure 8 shows a wider detection range when more Kinects are combined.

Following the detection range, the gait analysis using multiple Kinects should be in the middle of all sensors.

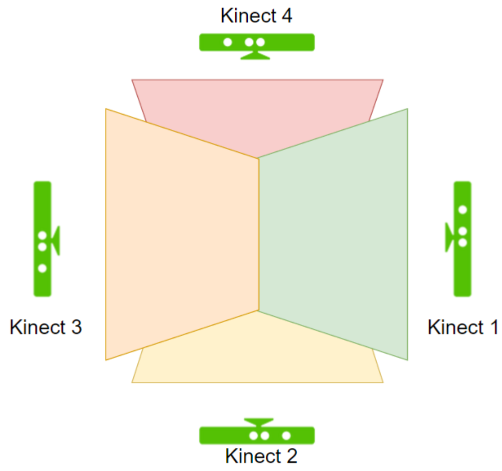


Figure 8. Multiple Kinects detection ranges

Thereafter skeletons from all Kinects can be aligned, synchronized, and a full 360o fused skeleton can be generated using matrix transformations and quaternion fusions [49].

Many authors used the Microsoft Kinect and multiple Kinects to estimate 3D human motion and gait analysis. [50] investigated the accuracy of a single Kinect for clinical measurement. This study has found that the Kinect can be used in a clinical environment and achieved maximum 3D difference of 5cm for all joints when compared with the VICON system. [51], proposed a Dual-Kinect tracking comparing with VICON with results of absolute error not exceeding 20mm.

Multiple Kinects systems are also used in rehabilitation and motion analysis. [52] proposed a multi Kinect assessment for quantitative gait against marker-based MoCap system to extract full body kinematics (it did not include inertial sensors) showing spatiotemporal gait similarity of 0.88 when compared with VICON. The results of this study concluded that a Multi Kinect system can provide accurate motion analysis. Although these authors found out that their system can track motion in two or more viewpoints, their system is not capable of track full 360^{o} motion and does not consider the view from the back, which is a limitation. These studies have the conclusion that due to the occlusion limitation of a single Kinect; a multiple Kinect system can be an alternative for motion analysis.

2.1.3.5 **Marker-less Systems and Gait Analysis**

The authors in [53] proposed a gait analysis system composed by only a single RGB camera. The methodology applied generates a silhouette using particles filtering from a synthetic image. The authors reported that the sample rate was quite low (20hz) and as a result, they could not get angle changes of more than 5° between two frames. They reported results for longitudinal displacement of the knee and ankle. Their comparison against a VICON system was presented via graphical differences with no calculations. Some movements and joints are occluded due to the limitation of using a single view camera.

In [54], a multi Kinect system was developed for gait assessment. This technique converted skeleton frames from a single Kinect into a feature vector. This work considered “centre of mass” (COM) as centre of hip, shoulder and spine joints. They also captured stride times, and angular velocities in different phases of stride. Their system was compared with reference values from Kinect and did not consider any other comparison method with a gold standard system like the VICON system. The results have shown that multiple Kinects can be applied to capture human movement and assess gait. They have applied the system to capture spatiotemporal gait variables and found correlation of 0.97 for right stride length, 0.83 for left stride length, and 0.92 for gait time.

In [55], the authors proposed a low-cost marker-less MoCap system using a single Microsoft Kinect to obtain 3D joint position and extract gait spatiotemporal features. Their method defined toe contact to mark starting and ending points of a full gait cycle (full walk) and generated gait variables. They considered the variables of speed, step length (distance between two steps), step time; stride length (distance between two strides), and stride time. This study defined what are some of the most important gait spatiotemporal variables in use today. They compared the system with the 3DMA (3D Motion Analysis) system [56] and concluded that poor detection of anatomic landmarks in lower body caused the system to be inaccurate in calculating some variables such as step time (diff between Kinect and 3DMA -0.17), and stride time (diff between Kinect and 3DMA -0.20).

In [57], a multi Kinect system was developed for gait assessment comparing results with VICON. The results have shown that multiple Kinects can be applied to capture human movement and assess gait. They have applied the system to capture spatiotemporal gait variables and found correlation of 0.97 for right stride length, 0.83 for left stride length, and 0.92 for gait time. The results of the study in this dissertation have shown correlation of 0.99 for gait time and 0.95 for right and left stride length.

Although these authors found out that their system can track motion in one, two or more viewpoints, their system was not capable of tracking full 360^o motion and did not consider the view from the back, which restricts the system to applications at frontal views. The gait system presented in this dissertation considers the full 360^o view from users and can capture 3D, spatial and temporal gait variables.

2.1.4 Wearable Sensors

The idea of a worldwide network of connected sensors that exchange information between them is quite broad and it is common to call the concept Internet of Things (IoT). Recently, there has been an explosion of consumer wearable technologies, such as fitness bands or smart watches and devices that provide diagnostic and monitoring information on movement and motion. These technologies are part of a field within IoT: the wearable [58]. The wearable industry is expected to have revenue of more than 50 billion dollars by 2023 [59]. However, the development of such sensors has been hindered by non-user considered design and complexities across several domains such as safety, communication, fitness, and health. Examples of connected sensors are Inertial Measurement Units, or simply called IMUs.

2.1.4.1 Inertial Measurement Units (IMUs)

Inertial sensors are devices capable of monitoring velocity and variations in acceleration by converting inertial measures, into some known physical change. The captured signal is then converted by a transducer and converted into an electrical signal. This electrical signal is subjected to linear and non-linear filtering processes to create an input signal estimate. The final output will represent a calibrated value of measured acceleration or velocity [60].

An Inertial Measurement Unit (IMU) is created when 2 or more inertial sensors are combined in the same circuit. An IMU is an electronic device capable of measuring different parameters of a body like acceleration, force, angular rate, and magnetic field around the object by combining accelerometers, gyroscope, and magnetometers (Fig.9 and Fig.10) [60, 61].

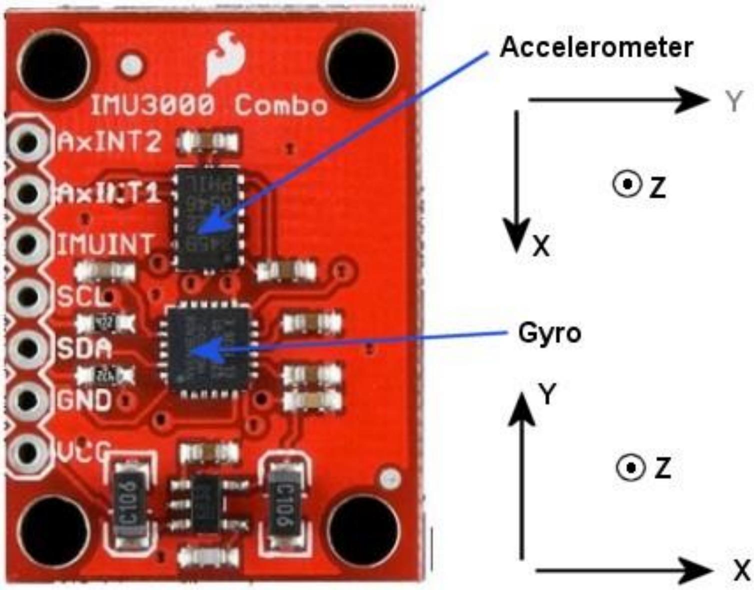


Figure 9. Accelerometer and gyroscope IMU. Available at [62]

In a single integrated circuit, each IMU has micro-machined mechanical structures forming mechanical transducers, responsible for carrying out the task of sensing. The sensor is composed of microstructures capable of giving analogical electrical signals corresponding to the forces to which the sensor was subjected [60]. For simple tasks, devices that provide digitized, digitally filtered, and processed signals can be used including those that store previous readings in memory, all independently, without the need of a main CPU [63]. Whether the sensor provides a raw output without any treatment or a ready-to-use processed output will depend on the characteristics of the chosen device and, the output [60, 61, 63].

The category of IMU is represented by three types of devices:

- Accelerometers: capable of measuring linear acceleration in the direction of a reference axis. Acceleration is the rate of change of velocity in time, represented in m/s^2 (meter per second squared).
- Gyroscopes: capable of measuring the angular velocity around a reference axis. The angular velocity is a magnitude representing the rate of change of the angular position in time, whose unit of measure in the International System is rad/s (radian per second).

- Magnetometer: capable of measuring the intensity, direction, and direction of magnetic fields in their vicinity. In general, they are used in geophysical studies related to the Earth's magnetic field and the magnetosphere.

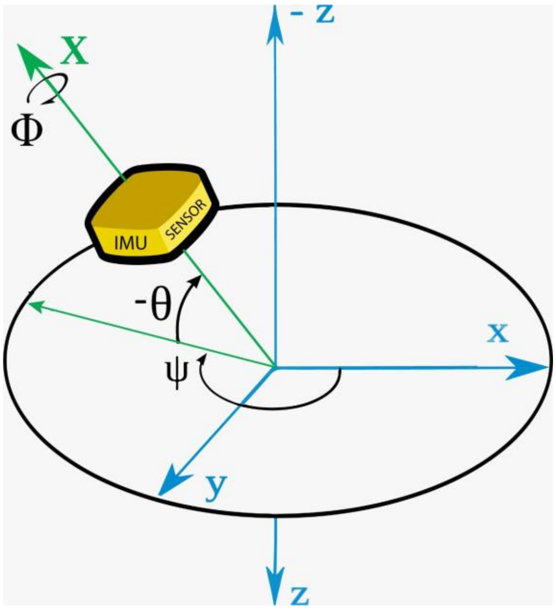


Figure 10. IMU and rotations

Accelerations and angular velocities are vector signals, having magnitude and direction. If only one component of the vector is measured, the sensor is characterized by 1D or an axis. If two or three components of the vector are captured, the sensor is characterized as a 2D or 3D accelerometer, respectively.

2.1.4.2 **IMUs in Gait Analysis**

The use of IMUs for human motion capture has been studied for some time. With the development of microelectronics, the integration of sensors has become more viable, and the miniaturization of inertial units has allowed their use in Biomechanics, and also in gait analysis[64]. Gait analysis using wearable devices like IMUs, can offer an inexpensive, accurate, and an efficient way to provide gait assessment for rehabilitation and in diagnostics to detect abnormalities in walking, due to medical conditions, and sports injuries [65]. [66] used inertial sensors to present a low-cost gait monitoring for 3 body segments, showing that 3D orientation can be obtained by using IMUs outside the lab in any unconstrained environment.

The most well-known application of IMUs in gait rehabilitation and assessment is the use of sensors for impact detection and motion analysis. The benefits of this application as a therapeutic has been published and include posture and balance corrections, increased locomotion capacity, and improved range of motion of the upper and lower limbs [67]. To perform biomechanical measurements, such as range of motion, it is necessary to incorporate more than one IMU so that angular evaluation is possible. The sensors are positioned at the midpoint of the limbs to facilitate this [68].

With the evolution of inertial sensors, human movement has been studied in diverse environments and situations like research, gaming and medical, making use of only a few IMU in contact with the body. In addition, collected data can provide some important gait variables such as acceleration, angular velocity, height, and movement direction.

In [69], the authors used 9DOF IMUs for gait temporal assessment and concluded that IMUs could be used to assess temporal gait parameters with high correlation between IMUs and gold standard systems (0.97 for gait time and 0.82 for stride time).

The authors in [70] developed a real-time estimation of temporal gait variables using 6DOF IMUs and have correlation results of 0.93 for stride time, and 0.97 for velocity against the GAITRite (GR) system [71]. These studies have shown that IMUs can offer a low-cost tool for temporal gait variables, even though they did not capture any three-dimensional information. To capture spatiotemporal and 3D variables of gait, a combined system using 3D points from Kinect and IMUs may be a low-cost alternative for gold standard gait systems.

Integrating inertial sensors with a single Kinect has been applied in rehabilitation and motion analysis. [72] and [73] are the closest to the proposed work found in the literature. These authors used a single Kinect integration with 6 DOF (Degrees of Freedom) inertial sensors for rehabilitation purposes in post-stroke patients. They found out that the integration is possible but further improvement in calibration and more degrees of freedom from inertial sensors is required (The developed system of this dissertation applies a 9DOF inertial sensor and Multiples Kinect). [73] has also used a single Kinect and inertial sensors to build a system to help post-stroke patients showing application in a clinical setting. However, no integration is described. Other authors fused a single Kinect for low-cost skeleton tracking and refined gesture recognition achieving an overall recognition rate of 93% [74, 75].

Considering these works and to the best of the author's knowledge, the novelty of the capturing system proposed in this work lies in the fact that: (a) no works in the literature have integrated IMUs with a fused Kinect skeleton from multiple Kinect by the combination of 3D points (x, y, z) and quaternion orientation (w, i, j, k) generating in a 360^o view; (b) presents a real-time wireless synchronization and streaming protocol for multiple IMUs; (c) supports easy set up and is low cost; (d) provides 3D and kinematic data with 9 degrees of freedom; (e) enables fully body reconstruction; (f) provides accurate join angles; and, (g) is marker-less and can be used in any environment. To examine the utility of the gait system, a comparison with the gold standard VICON was performed. Further in this document the developed gait system is introduced. The proposed system framework, signal processing, and experimental protocol will be also described.

2.2 Immersive Multimedia in Gait Analysis

Besides the capturing part of the system, feedback modules were designed for this project. The modules were composed by different technologies: haptic interface, AR (The network architecture also allows the use of other feedback modules). This section discusses some applications of immersive multimedia and the rationale behind the choice of haptic and AR feedback over other technologies.

2.2.1 Feedback Modalities

The existing literature presents various feedback mechanisms that are widely used across the literature. However, novel immersive technologies such as Augmented Reality (AR) are emerging that potentially have utility. AR, relatively speaking, is unexplored in terms of gait feedback and in this study, I aimed to evaluate how users perceive such feedback, as well as assessing the utility of AR compared to the state-of-the-art haptic feedback approach. In addition, current feedback technologies have some limitation in gait such as:

- 2D screens – This approach does not allow the user to walk freely in any direction they want, they always need to walk towards the screen and must have their head up facing the screen.

- Audio – In order to comply to the audio guidance, users need to clearly understand the guidance which can be confusing. The existing literature also highlights that visual based feedback has higher utility than audio for gait re-education [76].
- Expert guidance – It has many benefits, but requires the user to attend an expert clinic, the expert to be available and is based on subjectivity of the clinician.

These current tools have been shown to have utility but as discussed above they also have individual limitations which are motivations of the current study.

2.2.2 Haptic Interfaces

The term “haptic interface" refers to devices that allow the user to touch, feel or manipulate simulated objects in virtual environments and teleoperated systems. Haptic interfaces also use 3D displays and 3D stereo sound devices applied through images and sounds promoting the feeling of immersion within the virtual space [76]. In addition to user immersion, haptic systems must provide real-time interaction with the virtual environment and data transfer through a tactile interface. Examples of haptic interfaces include vibrotactile controllers, jackets, gloves, bracelets, and others (Fig. 11) [77, 78].

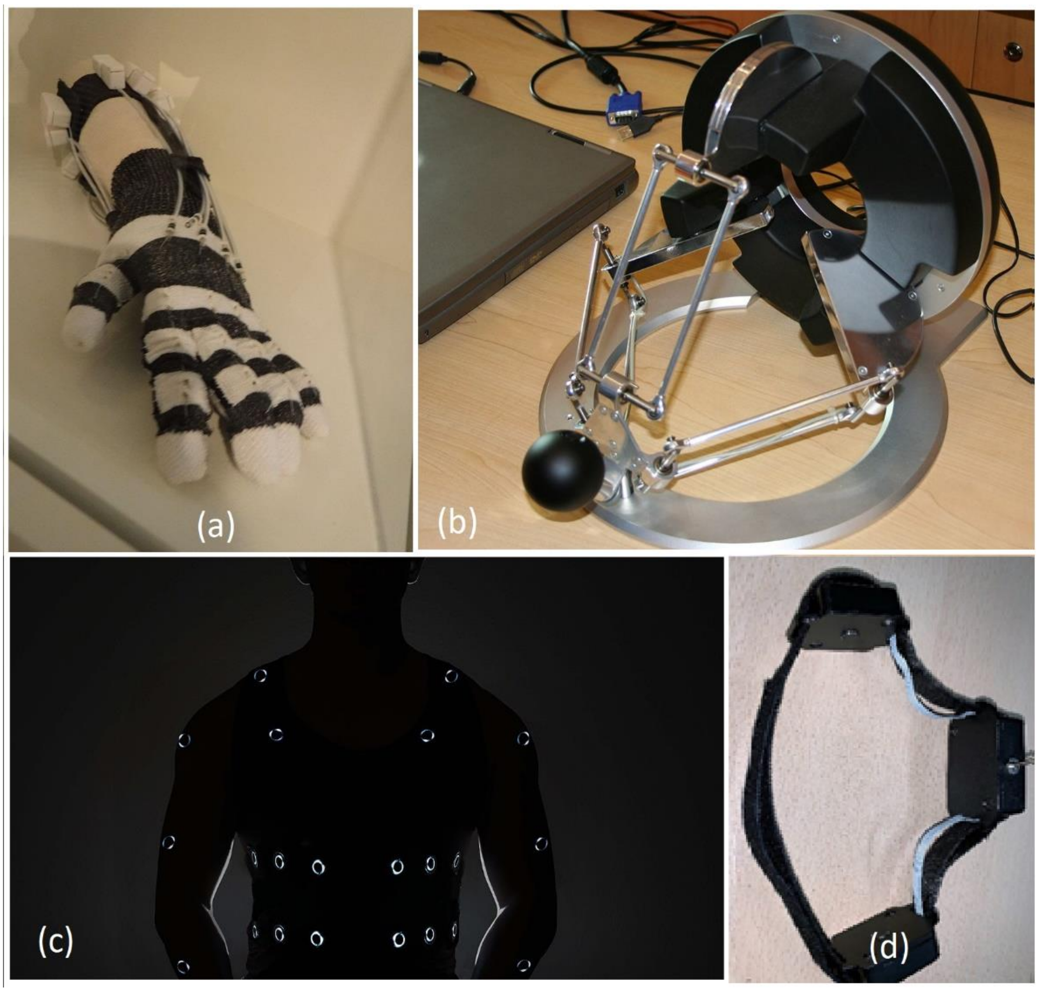


Figure 11. Haptic interfaces. haptic glove (15a), haptic controller (15b), japtic jacket (15c) Adapted from [79], haptic bracelet (15d)

Haptic feedback can be classified into three large groups as they provide: force feedback, tactile feedback, or self-sensing feedback. Each of them provides information to user regarding feedback interface depending on desired characteristics. Interfaces that provide force feedback provide data related to the hardness, weight and inertia of the virtual object [80]. The interfaces that provide tactile feedback allow users to acquire data such as the geometry of the virtual object, its roughness and temperature, among others. Finally, the interfaces that provide self-receptive feedback give information about user's body position or posture [81].

Haptic feedback has been studied in many works related to human activities [82], motor learning [83], and gait retraining [84]. Numerous works have compared haptic feedback with other modalities and have reported haptic: to be “less intrusive” than virtual reality feedback [85]; to be better in supporting task performance when compared to visual feedback for lower extremities [86] in gait; not to affect ecological validity of interaction compared with other modalities [87]; and, to be easier to understand and followed when compared to auditory and visual stimuli [76].

Haptic feedback was also used to enhance the realism of a walking experience in multimodal environments [88], which may inform the benefit of using it to enhance user experience in different applications (e.g. games, movies). Haptic feedback has also been used as an important tool in gait retraining for treatment of knee osteoarthritis [89]. In [90], closely aligned to the focus of this work, a gait re-training system employed haptic feedback to change gait parameters including varus/valgus misalignments. They reported the ability of participants to perceive haptic feedback. They also highlighted issues whereby users were confused when receiving more than one feedback simultaneously (i.e. on different parts of the body). The system and results served as basis for this work on informing the use of haptic feedback to capture and improve gait parameters including knee alignment. Beyond the study mentioned above, there are other feedback modalities that could be used in gait re-training such as Virtual and Augmented Reality.

2.2.3 Virtual and Augmented Reality

Every decade, the technological scenario reformulates into a new and important cycle. In the 80s, PCs changed the world and the way companies and people organize data. The 90's were important into connecting everyone through the internet. The early 2000 were important with the development of smartphone devices [91].

As with this we move into a new cycle, in addition to the use of wearable devices, haptic interfaces, Virtual Reality (VR), Augmented Reality (AR) and Mixed Reality (MR) are on the rise (Fig. 12). These are immersive technologies that already allow us to interact with others and experience the world like never before.

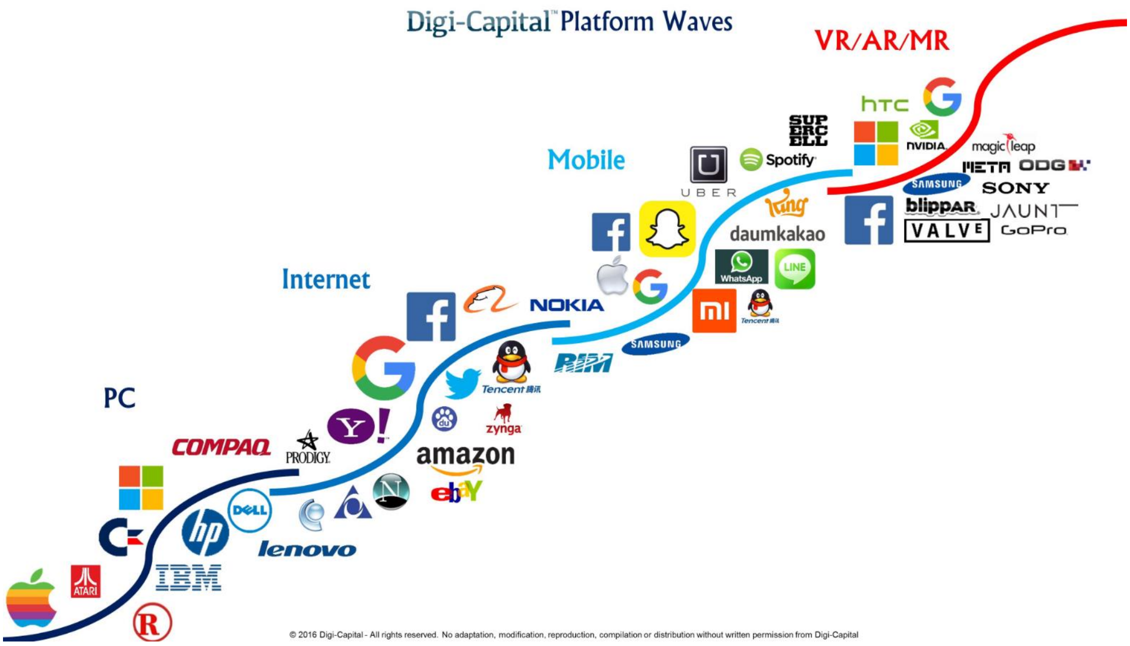


Figure 12. Platform Waves history. Available in [91].

2.2.3.1 **Virtual Reality**

Virtual Reality (VR) is an artificial environment created from software that can deceive user's senses. VR technologies include visual, sound and even tactile effects to immerse users into the environment. Virtual reality allows complete immersion in a simulated environment, with or without user interaction [92].

Currently, virtual reality is based on stereoscopic displays such as glasses and Head-mounted Displays (HMD) (Fig.13), being mostly disseminated for entertainment. However, the concept encompasses much more than visual effects and it has been around for a long time. VR is not just for games and entertainment, but its use is increasing for many business and services [93]. VR is definitely changing the industry of sport, athletes training, mental health, medical training, and education. It represents changes in the way people may interact in the future [94].

Figure 13. The Oculus Rift CV1 (Consumer Version 1), a virtual reality headset made by Oculus VR and released in 2016. Available at [95].

VR is a technology with applications in diverse areas such as health, retail, education, real estate, military, live events, entertainment, and engineering. In health, many applications are already being carried out by many professionals and companies specialized in patient care. VR technology is utilised for training health professionals such as doctors, nurses and caregivers of patients. It allows the recreation of real work situations efficiently, with low cost, and, most important, at no risk to a patient [96].

As well as exercise simulator games, very popular on virtual gaming platforms, VR can be used in therapies in which patients need stimuli to move. The use of virtual reality in the form of interactive games or even just in other scenarios increases the engagement of therapy, which becomes more interesting and stimulating for the patient [93]. In addition, the procedure assists the therapist, who can have access to the patient's movement data, which allows them to assess the effectiveness of treatment, and subsequently alter exercises and specific parameters based on patient performance, ensuring a therapy as well. more exclusive for different people [97]. Even though VR is an emerging technology, it is quite limited in some applications that requires awareness of the body and movements such as sports and gait re-training.

2.2.3.2 **Augmented Reality**

Augmented Reality (AR) is a technology that allows the combination and insertion of virtual contents in the real environment. This insertion is done in real time through small screen(s) close to users' eyes, providing an experience of digital elements in the real world [98]. AR systems present the following properties: combines real and virtual objects; runs interactively in real time; aligns real and virtual objects with each other; and, can be applied to all senses, including hearing, touch and smell [99].

A well-known example of AR is the mobile game Pokémon Go by Niantic and The Pokémon Company International (Fig. 14) [100]. In this sense, real elements captured by a mobile camera and virtual AR elements coexist promoting high user experience.

Figure 14. Pokémon GO. In this game augmented elements are mixed within the real world through smartphone cameras. Available at [100].

The use of AR is not restricted to smartphones. There are special devices called Smart Glasses that can always be worn, assisting the user with information, calls, messages, GPS guidance, among others. This technology is still actively being researched, with companies trying to produce the best option for customers, resulting in multiple innovative models designed for different purposes [101]. Generally, smart glasses aim to provide life monitoring services, as well as the creation of a platform to take pictures and make more authentic video clips. They can also be equipped with AR technology, to help you in everyday life at home or at work.

Smart glasses work through a combination of screens, sensors, and accelerometers, along with smart software and internet connectivity to increase utility. They tend to come with touchpads and / or voice controls to help users navigate the software that controls them and can be incorporated either into the glasses, a handheld device, or both.

Currently, there are a few devices available, but most of them are not really intended for consumer use but for development purposes. Epson Moverio (Fig. 15) is an example of smart glasses designed for professional use and development and was used in this work [102].

Figure 15. Epson Moverio BT-300 - Augmented Reality Glasses.

Some authors have applied AR in gait analysis in different ways. In [103], a low-cost gait analysis system was developed using AR markers and a single video camera. The AR markers were used to track body segments and capture gait variables. Even though the authors achieved calibration and accurate tracking for gait angles (errors of spatial parameters below 23mm), they highlighted the use of markers as a limitation (e.g. this system could not be used for treadmill walking for example). The use of different AR devices was also reported for guided walking over obstacles in [104, 105]. This research indicated that novel AR technologies can be used to improve elements of walking performance, such as body stability, gaze, and locomotor control [106, 107].

Considering these works, the use of AR for gait feedback has not been deeply explored. There are some exploratory works that suggest employing AR for gait retraining. The results reported in [108] indicated a significant improvement in gait and movement skills when compared to a 2D monitor. Other research examining the use of AR in gait posture training [109] reported statistically significant improvements in posture, balance, and velocity. In [4], a gait retraining system was developed to modify footprint parameters. The authors concluded that AR could help to quickly modify user's footprint parameters. Although these works make a valuable contribution, there was no qualitative metric employed that informs if users were satisfied or enjoyed the feedback experience. This is critical because it informs designers about how the users enjoy, engage, and experience such systems. Consideration of the current literature and the lack of deep exploration of AR as a tool to provide gait feedback, it was chosen as one feedback module of the system proposed in this dissertation. All the different feedback approaches have advantages and disadvantages. Such issues are validation for why QoE assessments of such feedback mechanisms are required.

2.3 Quality of Experience (QoE)

The term "quality" refers to a set of attributes that meets customers' needs and maintains a high standard for products and services [110]. Quality in relation to products and / or services takes several definitions such as efficiency, added value, legal requirements, durability, absence of defects, and more [111]. Even within quality evaluation methods, finding a quality assessment methodology that considers system, human, and context factors can be a challenge. The QoE framework defined by [112] states:

"The degree of delight or annoyance of a person whose experiencing involves an application, service, or system. It results from the person's evaluation of the fulfillment of his or her expectations with respect to the utility and/or enjoyment in the light of the person's context, personality and current state."

QoE is used to understand user perceptual quality of multimedia experiences. It measures total system performance using subjective and objective measures not only for customers but also for users of a specific device for example. QoE has grown now into a multidisciplinary research field on user perceived QoE, evaluating the relationship of a wide range of human, context, and system factors (Fig. 16).

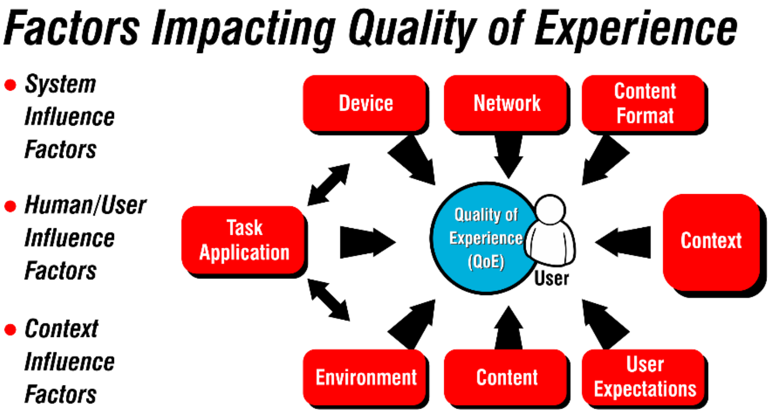


Figure 16 - Factors influencing user QoE, adapted from [113]

QoE takes into consideration three categories of factors that influence experience. It considers how system, human and contextual factors contribute to a user's perceived quality of an application, service or system [17]. As this study aimed to assess knee misalignments, varus/valgus were defined as context influence factors of QoE.

Previously literature has identified that incidence of varus/valgus differs across gender [114, 115], thus gender is considered a human influence factor. Anatomical differences between males and females lead to differences in knee alignment. Differences in lower extremity alignment are potentially a causal factor in the development of anterior cruciate ligament injuries in females [116]. Females, in general, have wider hips than males, which can cause kinematic abnormalities such as knee valgus/varus, leading to increased risk of injury [117]. An example of how the three main factors are applied in this work is shown in Fig. 17.

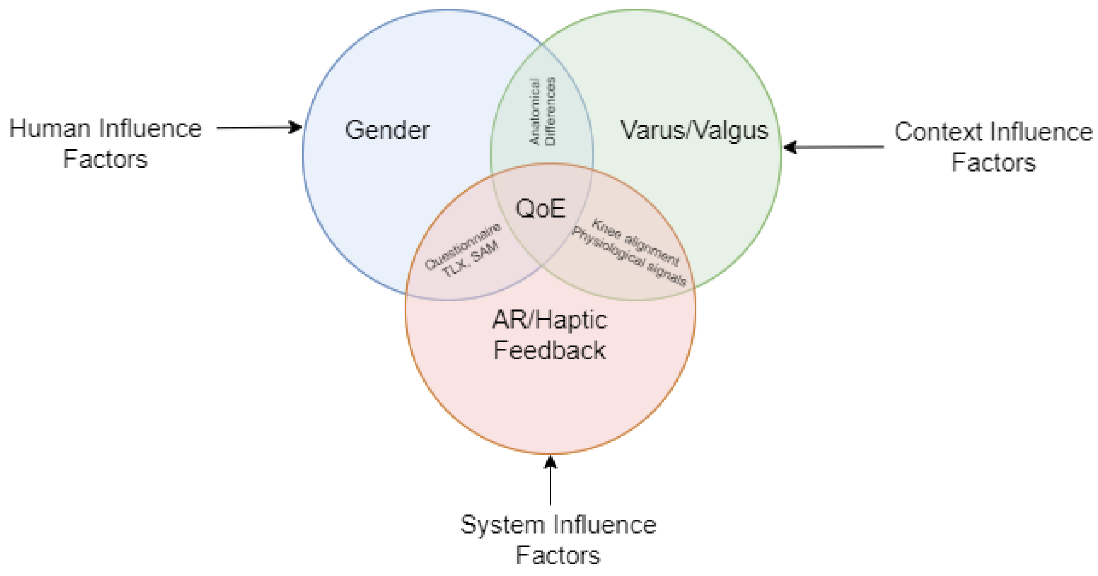


Figure 17. QoE influence factors of gait feedback system.

2.3.1 Methods of Evaluating QoE

Evaluating user's QoE involves taking each user state and translating it into information or a model. There are several ways of evaluating quality such as the use of questionnaires and instruments that can quantify user's physiological state. These mechanisms are divided into explicit, implicit, and objective measures.

2.3.1.1 **Explicit Measures of user QoE**

Explicit measures are directly asked or captured from participants and are essential for QoE studies. Examples include the use of questionnaires, where the participant's opinion, or experience is quantified objectively. Several authors have used QoE assessment in multimedia systems as a paradigm to quantify how various factors of the system influence perceived quality levels from the user perspective. In [118], user QoE levels were compared in an immersive Virtual Reality and Augmented Reality applications. A sample size of twenty-one participants was divided randomly into two groups. Both objective and subjective metrics were gathered. The authors considered system, psychological, and user factor to evaluate quality. The QoE evaluation suggested that users felt safer and accustomed with the use of AR when compared to virtual reality. This was another indication on the use of AR for this study.

In [119], a QoE evaluation of a motor skills rehabilitation game was developed. The authors have assessed QoE through user engagement, task success, interaction, and socialization. This study reported that high QoE scores can be linked to higher performance. These works demonstrate the need for a qualitative study examining different applications, such as gaming performance, and rehabilitation of impaired children.

In order to evaluate quality, subjective assessment can guide companies and researchers to make better decisions and evaluate user's opinion. In practice, this strategy involves those who carry out the research and, of course, willing participants.

2.3.1.1.1 ITU-T Standards (MOS, ACR, DCR)

The ITU Telecommunication Standardization Sector (ITU-T) [120] is a group of experts around the world that gives standards and recommendations for works in Information Communication Technology (ICTs), which also gives support for QoE studies. The "*Methods for Objective and Subjective Assessment of Quality*" document from ITU-T, proposed various questionnaires as subjective evaluation tools. These employ opinion scores such as Mean Opinion Score (MOS), Absolute Category Rating (ACR), and Degradation Category Rating (DCR).

ITU-T recommends the use of ACR questionnaires for listening tests, and tests that evaluate speech. The category judgment is done one at a time and rated independently on a scale after the participant views or listens to a sample. The method leans to a low-quality sensitivity. The quality scales are done with 1-5, 1-9 or 1-11 ranges.

The DCR questionnaire is a modified version of the ACR procedure, which tends to a high-quality sensitivity. The procedure is done by rating a 5-point degradation category scale for speech evaluation (e.g. "sample is inaudible", "sample is annoying").

One of the main instruments that mediates this relationship and makes it possible to obtain subjective information is a MOS questionnaire, which was used in this work due to its good representation of a group opinion.

2.3.1.1.2 MOS Questionnaires

In QoE studies, MOS questionnaires can represent the overall quality of a stimulus or system [120]. MOS is expressed as a numerical representation. It can be represented by different rating ranges such as 1-5, 1-7, 1-100 [120]. The MOS is calculated as the arithmetic mean over individual measures as in (1).

$$MOS = \frac{\sum_{n=1}^{N} Measure_n}{N} \tag{1}$$

Where Measure are individual scores for every variable or question for a number N of subjects.

Many authors used questionnaires in QoE evaluation [15, 118, 121, 122]. The ITU Telecommunication Standardization Sector (ITU-T) [120] provides recommendations for work in Information Communication Technology (ICTs) and gives support for QoE studies. The authors in [121] have used a MOS questionnaire to evaluate experience for an immersive VR environment. This was a study that explained that you can compare different groups using the same questionnaire. The study also informed a capturing protocol that can be used consistently in QoE studies.

MOS questionnaires can also be used to evaluate specific quality factors such as system utility, usability, immersion, and interaction [123]. The authors in [124] showed that questionnaires can be used to evaluate how system usability can influence gaming QoE. Every study is different, and the researcher should decide which questionnaire to use. There is no standard questionnaire, so quality assessment can be a hard task despite the flexibility of the assessment [125]. The development of the MOS questionnaire in this dissertation will be discussed further in this document.

Beyond MOS questionnaire and objective measures, there are also some standardized questionnaires such as the NASA-TLX and SAM that provide good understanding on user`s arousal and cognitive workload. The use of these subjective metrics is widely validated in literature. Works as [126-128], report different studies using NASA-TLX and SAM questionnaires and are also metrics for QoE studies [129].

2.3.1.2 **Self-Assessment Manikin Questionnaire**

The Self-Assessment Manikin (SAM) questionnaire evaluates elements of emotion such as valence (pleasure), arousal, and dominance. Valence, or hedonic tone, is the level of pleasure or annoyance to a situation, event, or object. Arousal refers to the level of excitement after the occurrence of an event, and dominance refers to the dominant control of the emotion [130]. Higher scores of the SAM questionnaire represent greater excitement and emotion control. An example of a SAM scale is shown in Fig. 18.

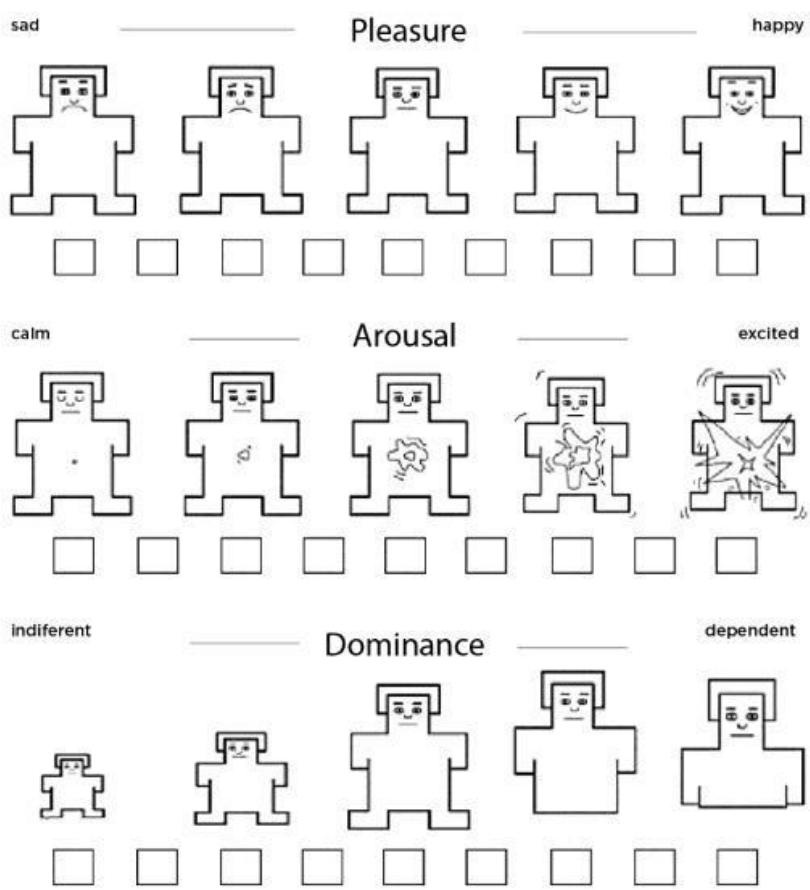


Figure 18. SAM questionnaire example. Available at [130].

This type of analysis can represent different levels of emotion and give the researcher a better understanding of the target system, group, or object. An example is the use of VAD (valence arousal dominance) plots for emotion analysis as in Fig. 19.

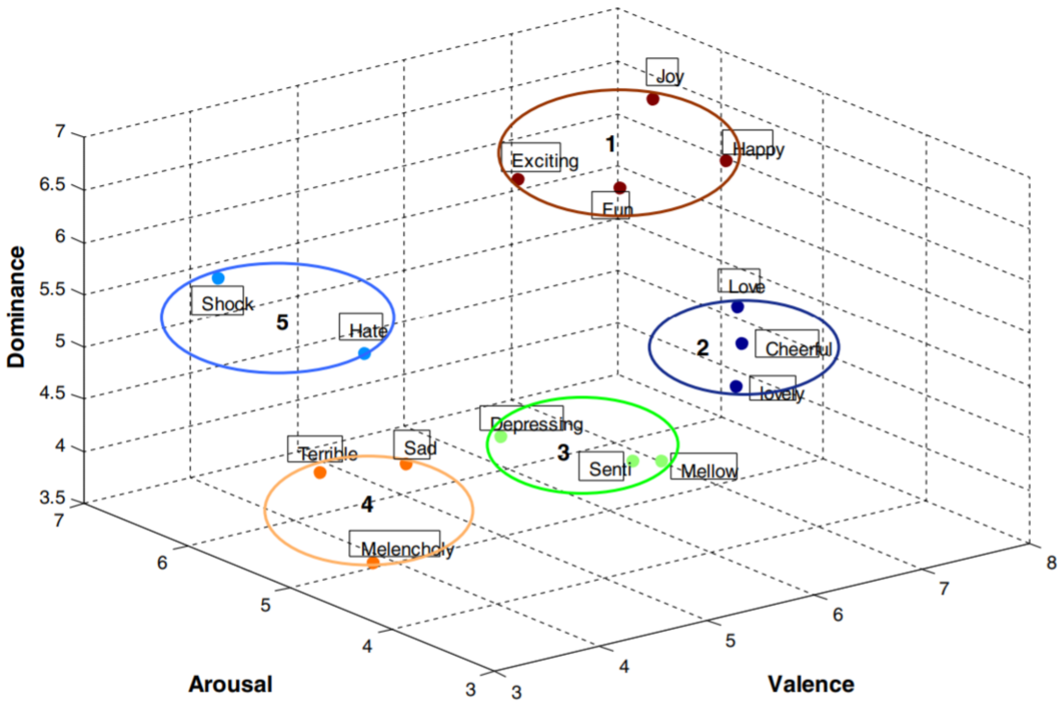


Figure 19. VAD graph. Extracted from [130]

2.3.1.3 **NASA-TLX**

When assessing feedback systems developed for the purpose of learning, there is a need to assess the workload experienced when completing a task. The Nasa-Task Load Index (NASA-TLX), is a multi-dimensional scale that can estimate workload [131]. This validated questionnaire is widely used in many QoE studies and consists of two parts that assess mental demand, physical demand, temporal demand, performance, effort, and frustration. The description of each parameter is shown in Fig. 20.

Mental demand	How much mental activity was required? Was the task easy or demanding, simple or complex?
Physical Demand	How much physical activity was required? Was the task easy or demanding?
Temporal Demand	How much time pressure did you feel due to the pace of the task? Was the pace slow or rapid?
Overall Performance	How successful were you in performaing the task and how satisfied were you with your performance?
Frustration Level	How irritated, stressed, or annoyed were you versus relaxed, content or complacent during this task?
Effort	How hard did you have to work (mentally and physically) t oaccomplish your level of performance?

Figure 20. NASA-TLX descriptions.

2.3.1.4 **Implicit Measures of Experience**

Implicit measures are used to evaluate meaningful psychological outcomes. These variables are usually captured indirectly and therefore do not ask people to directly report their responses. In QoE studies, the use of physiological measures is important to assess experience, cognitive workload, emotion, etc. In terms of multimodal systems, there are some authors using physiological signal assessment as part of the QoE evaluation [122, 129, 132-134]. These authors evaluate from a user experience context, electroencephalography (EEG) sensors [135, 136], functional near-infrared spectroscopy (fNIRS), and others [132]. These studies are contributing to the QoE research by creating models that incorporate technical, contextual, and human factors in design and evaluation.

There are other authors using physiological measurements in QoE [137], evaluating virtual and AR immersion [134], and feedback to users [138]. In a multimodal system, it is possible to evaluate system feedback in QoE factors for training and education [139]. In the work of [140], a new immersive Virtual Reality (VR) gaming system was developed, and users learned how to operate a real forklift through simulation. This example can be applied in gait re-education using feedback parameters like augmented AR, and haptic feedback.

The QoE evaluation of a gait system can assess how users are dealing with sensors, if they are having clear feedback, if the sensors are comfortable, user centered, provide valid ecological data, and providing context-based and appropriate feedback to patients and to clinicians. Explanation on how physiological signals were used in this study will be presented later in this document.

2.3.1.5 **Objective Measures**

Objective measures refer to a set of quantitative variables used in the analysis and description of a study subject. This type of analysis may me more accurate since the observation is more controlled that a qualitative analysis [141]. In this study, the objective measures were variables related to a person's gait and feedback performance.

For gait, the captured variables were gait angles such as hip and knee flexion, trunk angles, and tibia angles (for valgus/varus feedback). Other variables included spatial variables like gait and stride lengths, and temporal variables such as gait cycle time, stride times, and velocity. These variables were captured by different motion capture system as used as part of the motion capture analysis.

Variables related to performance included the number of varus, valgus, and misalignments (assesses through tibia angles). The time in each misalignment was also captured to evaluate if after receiving feedback, the participant reduced the time in misalignment. The purpose of the objective evaluation was to see how participants objectively reacted to each feedback modality (to check if there was any improvement after feedback).

2.4 Final Considerations

Considering existing literature, the justification of the importance of this study goes beyond the topic of QoE and biomechanics. It is expected that this work along with all published works will serve as a basis for future researchers within the health arena. This may help with the development of new rehabilitation procedures using augmented, real-time, biofeedback.

The existing literature presents various feedback mechanisms that are widely used in many studies. However, novel immersive technologies such as AR are emerging that potentially have greater utility. AR is relatively speaking unexplored in terms of gait feedback and in this work, we aim to evaluate how users perceived the feedback and the utility of AR compared to the state-of-the-art haptic feedback approach. In addition, current feedback technologies have some limitation as in (i) 2D screens, which do not allow the user to walk freely in any direction they want. Users need to always walk towards the screen and must have their head up facing the screen; (ii) Audio, users need to clearly understand the guidance which can be confusing. The existing literature also highlights that visual based feedback has higher utility than audio for gait re-education;(iii) Expert guidance has many benefits, but requires the user to attend an expert clinic, the expert to be available, the additional cost of paying an expert,, and is based on the subjectivity of a clinician's interpretation of patient movement.

These current tools have been shown to have utility but as discussed above they also have individual limitations. In order to evaluate AR feedback regarding these limitations, the proposed study provides information via objective analysis (e.g. improvement after AR feedback) and subjective analysis such as questionnaires to assess the utility of using AR (including its limitations). AR is shown to be portable, wearable and immerses the user.

In consideration of the above discussed body of literature, the presented work is novel, as a QoE assessment has not previously been completed for gait retraining using augmented biofeedback. Also, the evaluation and analysis of users' QoE (self-reported measures and objective measures) of Haptic and AR feedback modalities as part of a gait analysis system has not been previously examined and is important in order to establish best practice. The focus is on comparing subjective and objective metrics for correcting knee alignment with these two different feedback modalities (Haptic and AR).

3 3D Marker-less System for Gait Analysis

3.1 Study Aims

Before developing the gait feedback system, it was important to evaluate different Motion Capture (MoCap) systems to decide what would be the ideal capturing system to provide feedback. The main aim of this study was to evaluate if motion analysis could be achieved by the integration of inertial devices and marker-less Motion Capture and determine how accurate such system could be in comparison to a gold standard system such as the Vicon system. To demonstrate the utility of the developed system, a comparison report with the VICON system was conducted.

As part of the system comparison, the application of the gait system in gait analysis to extract gait features by combination of inertial and 360^{o} skeletons was evaluated. In addition, the system overview outlines the designed and developed synchronization modules, and real-time streaming protocol and fusion of accelerometer, gyroscope, and magnetometer data for quaternion representation in R^4.

In the next section, the gait system and discussion of results of system testing are presented. The proposed system framework, signal processing, and experimental protocol is also described.

3.2 Motivation

Although gait standard systems such as VICON system have excellent precision, as outlined in the related work section, the cost of equipment can be inhibitive. There may be some situations where high-performance systems like the VICON are not required. The high cost and specific installation make it difficult to be used in clinical applications for example. Also, the need for reflective markers can be an obstacle and invasive for human analysis in elders and persons recovering from orthopaedic surgeries. Constructing a 3D multimodal motion analysis system that can provide valid data using inexpensive motion capture devices like the Microsoft Kinect and inertial sensors, can be an alternative to these expensive systems for motion analysis. Hence, the aim of this study was to evaluate if a system which combines marker-less 3D motion capture with low cost inertial sensors provides an accurate method of human motion capture.

Accurate gait analysis is important in sports analysis, medical field, and rehabilitation. Although gait analysis is performed in several laboratories in many countries, there are many issues such as: (i) the high cost of precise Motion Capture systems; (ii) the scarcity of qualified personnel to operate them; (iii) expertise required to interpret their results; (iv) space requirements to install and store these systems; as well as difficulties related to the measurement protocols of each system; (vi) limited availability (vii) and the use of markers can be a barrier for some clinical use cases (e.g. patients recovering from orthopaedics surgeries).

After comparing the multimodal gait system as stated in the first publication ("*An Evaluation of a 3D Multimodal Marker-Less Motion Analysis System*"), some questions regarding gait variables needed to be analysed, including an updated literature review. After some adjustments, the aim is to update the multimodal gait system in a way that it provides gait variables as part of a full gait analysis system. A gait comparison with results from the VICON system for gait spatiotemporal variables: gait cycle time, stride time, gait length (distance between two strides), stride length, and velocity was performed, which are reported in the second publication of this study ("*Human Gait Assessment Using a 3D Marker-less Multimodal Motion Capture System*."). The system was also evaluated on its ability to assess knee and hip joint angles accurately through bootstrap analysis. In the next section, the gait system is introduced, and results from the first and second comparison are discussed.

3.3 Study overview

3.3.1 First Analysis - 3D Motion Analysis System

Motion analysis is a technique used by clinicians that quantifies human movement by using camera-based systems. Marker-based motion analysis systems have been used across a variety of application domains, from Interactive 3D Tele-Immersion (i3DTI) environments to the diagnosis of neuromuscular and musculoskeletal diseases [142, 143].

In this study, from a system perspective, a cheaper, alternative and more accessible system for motion analysis is presented. The ultimate aim is to use the output of this multimodal gait analysis system as part of an immersive gait feedback tool. In real-time, it can advise the user on their gait performance (as well as potentially providing accurate clinical data to clinicians).

With the initial focus on the capture system, a novel multimodal gait system that integrates Multiple Microsoft Kinects (employing RGB-D cameras) with multiple IMU sensors was developed and evaluated. A comparison of this system with the VICON system (the gold standard in motion capture) is presented. The marker-less motion capture system combines data from 4 skeletons generating 3D and complete 360 degrees in view skeleton. The analysis found component similarity of 97% for knee angles and 98% for hip angles. These results show that in the context of our use case, this system can, by combining data from the Multi Kinect system and IMUs, provide a cheaper, sufficiently accurate and more accessible human motion analysis system. More details of this study are shown below.

3.3.2 Second Analysis – Gait Analysis

In general, gait analysis involves the measurement, processing, and systematic interpretation of biomechanical parameters that characterize human movement. Through gait analysis, it is possible to identify limitations in movement and provide information to guide rehabilitation and prehabilitation procedures for orthopaedics surgeries. Currently, gait analysis is performed in biomechanical laboratories. The data from three-dimensional kinematic systems can be obtained through synchronized infrared and high-speed cameras [144]. It is also possible to capture ground reaction force data via force platforms[145]. The combination of joint movement and angles, in addition to spatiotemporal kinematic and individual anthropometric characteristics, can be used to describe gait. All these variables can be assessed through capturing technologies[18].

In this study, a gait comparison of the multimodal system in terms of gait spatiotemporal variables is presented. The novel multimodal system combines data from inertial and 3D depth cameras and outputs spatiotemporal gait variables. A comparison of this system with the VICON system (the gold standard in Motion Capture) was performed with gait spatiotemporal variables: gait cycle time, stride time, gait length (distance between two strides), stride length, and velocity. The system was also evaluated with knee and hip joint angles measurement accuracy. The results show high correlation for spatiotemporal variables and joint angles inside the 95% bootstrap prediction when compared with VICON.

The remainder of this chapter is structured as follows: discussion of results and comparison across some related work, conclusion which includes future study and potential applications.

3.3.3 Comparison with literature

Marker-less MoCap technologies have being used in gait analysis to detect gait events and in rehabilitation. Some marker-less technologies apply RGB cameras in gait. In [146], a 2D marker-less gait analysis was proposed using a single depth camera. Their system had an upright calibration protocol and tracks pelvis and feet segments. They compared their results with a marker-based technology with correlation between 0.82 and 0.99. Their system contained spatiotemporal variables and stride time error less than 0.02s.

The authors in [53] have proposed a gait analysis system composed by only a single RGB camera. The methodology applied generates a silhouette using particles filtering from a synthetic image. The authors reported that the sample rate was quite low (20hz) and as a result, they could not get angle changes of more than 5^{o} between two frames. They reported results for longitudinal displacement of the knee and ankle. Their comparison with the system with VICON system was presented via graphical differences with no calculations. Some movements and joints are occluded due to the limitation of using a single view camera.

In[54], a multi Kinect system was developed for gait assessment. This technique converted skeleton frames from a single Kinect into a feature vector. This work considered “centre of mass” (COM) as centre of hip, shoulder and spine joints. They also captured stride times, and angular velocities in different phases of stride. Their system was compared with reference values from Kinect and did not consider any other comparison method with a gold standard system like the VICON system. The results have shown that multiple Kinects can be applied to capture human movement and assess gait. They have applied the system to capture spatiotemporal gait variables and found correlation of 0.97 for right stride length, 0.83 for left stride length, and 0.92 for gait time. The results of the gait system from this dissertation have shown correlation of 0.99 for gait time and 0.95 for right and left stride length. In this work, the multimodal approach (optical mark-less combined with inertial sensors) was strictly compared with the marker-based VICON system.

As shown in the literature review, a lot of studies used MoCap systems in gait. For instance, [55] shows a low-cost marker-less MoCap system to extract gait spatiotemporal features. They considered the variables of speed; step length (distance between two steps); step time; stride length (distance between two strides); and stride time. This was an indication on the variables needed to evaluate gait.

In [57], the authors have applied the system to capture spatiotemporal gait variables and found correlation of 0.97 for right stride length, 0.83 for left stride length, and 0.92 for gait time. The results from the developed gait system in this dissertation showed correlation of 0.99 for gait time and 0.95 for right and left stride length. Although these, authors found out that their system can track motion in one, two or more viewpoints, their system was not capable of tracking full 360º motion and did not consider the view from the back. The proposed gait system from this dissertation considers the full 360º view from users and can capture 3D, spatial and temporal gait variables.

The first study dealt with fusing IMU and multiple depth sensors for angles and principal component analysis of knee and hip, which resulted in comparison across individual sensors. The second study, which is available at [147], presents the evaluation from a gait perspective in terms of spatiotemporal variables. In the next section, the gait system is introduced. The chapter also contains results and discussion of system testing. The proposed system framework, signal processing, and experimental protocol is also described.

3.4 System Design

The system combines unit quaternions from each Kinect joint with quaternions from 4 inertial measurement units to promote integration. The system was used to measure 3D points of 12 joints from the Kinect fused skeleton and flexion-extension angles of the knee and hip in a walking trial in 10 participants with 12 trials per participant.

The gait assessment system captures and combines metadata of 4 MS Kinect cameras, and data from 4 Shimmer IMU. The multimodal architecture is composed by a Multi Kinect module, and an IMU module as per Fig. 21. It also contains real-time synchronization protocol and an orientation filter [148].

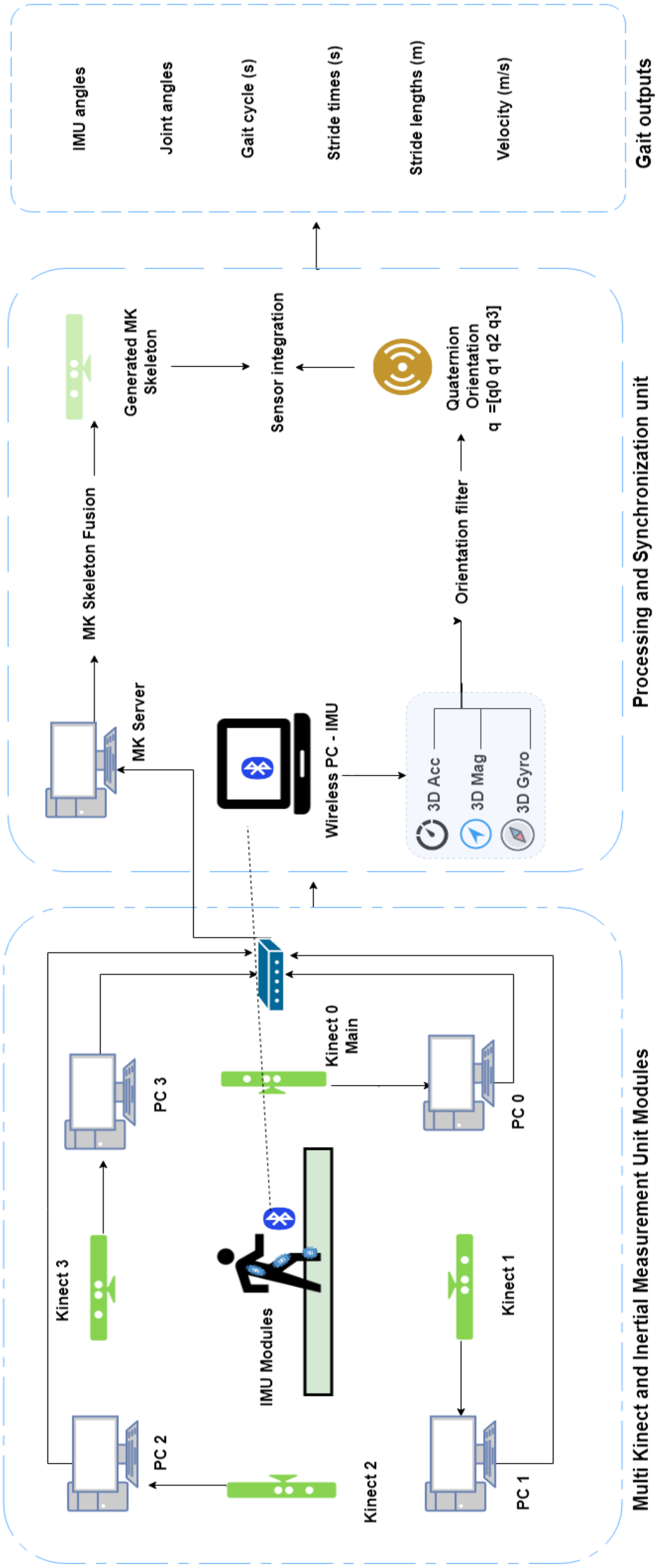


Figure 21. Gait System diagram containing 4 Kinect skeletons and 4 IMU data as inputs and a fused 360o skeleton, angles, and gait spatiotemporal variables as outputs.

3.4.1 Multi Kinect Module

Being aware of the limitations of a single Kinect, such as occluded joints and limited area of movement (only front view), a module containing 4 MS Kinects was developed as per Fig. 21. The module also captured spatiotemporal gait variables. Each Kinect was powered by its own computer (4 quadcore Intel Core i7, 16GB DDR3 RAM, 3.2Ghz and Graphics processing unit). Each Kinect was also connected to the master server which processes the data from the Kinects and generates the fused 3D skeleton. Each Kinect captures a skeleton from one view perspective. The angle range of the Kinect is 57.5° horizontal and 43.5° vertical [44]. The multi-Kinect fusion enables full human body motion capture in 4 views.

The multi Kinect system contains 3 components: input, processing, and output. The input component consists of 4 skeletons (one for each Kinect). The processing component is responsible for synchronization, calibration, noise reduction, and skeleton fusion as in [149]. The output component returns the original 4 skeleton data and a fused 360° skeleton. For calibration purposes, all Kinects are kept at same height (0.8 meters), and the distance between Kinects in a square arrangement is 4.1 meters. The diagonal distance is 6m. This arrangement is kept for all experiments to provide consistent data (Fig. 22).

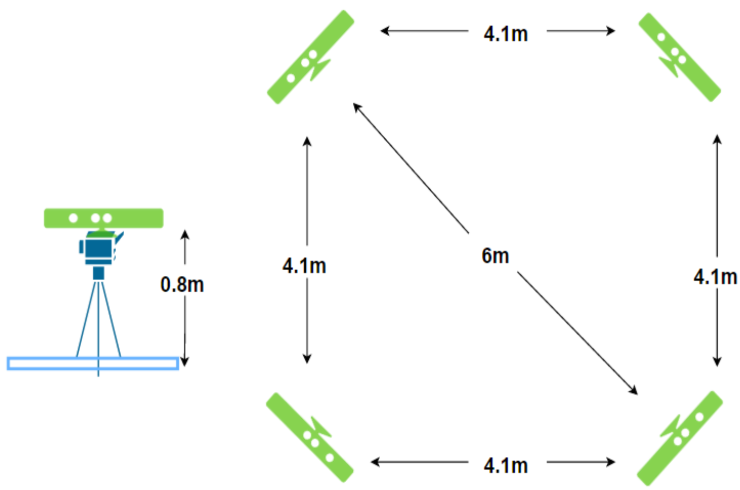


Figure 22. Kinect arrangement setup

To use skeleton data of 4 Kinects, the coordinate transformation between each Kinect into a “master” Kinect must be performed. For this transformation, the frontal Kinect (K0xyz) is accepted as the “master” Kinect and all other Kinects must refer to that 3D system. Using the coordinate transformation relationship as per eqn. 3, one Kinect's skeleton coordinate system can be transformed to the second Kinect's skeleton coordinate system by applying a transformation matrix. As a result, the skeleton coordinates in both Kinect skeleton are representing the same coordinate data system.

To discover the coordinate transformation matrix, a closed-form solution using unit quaternions is adopted to get a 4×4 transformation matrix [150] as in (2).

$$M_{AB} = \begin{pmatrix} R_{[0][0]} & R_{[0][1]} & R_{[0][2]} & Tx \\ R_{[1][0]} & R_{[1][1]} & R_{[1][2]} & Ty \\ R_{[2][0]} & R_{[2][1]} & R_{[2][2]} & Tz \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{2}$$

Considering:

a) M_{AB} – 4x4 transformation matrix to change one local Kinect A into a global coordinate B.

b) $R_{[m][n]}$ – The 3x3 rotation matrix

c) T – The 3x1 translation vector

To discover the transformation matrix of each Kinect (local coordinate system) into the K0 global coordinate system, (3-4) should be applied as per:

$$Bi = sR * Ai + T \tag{3}$$

<u>or</u>

$$\begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = s \begin{pmatrix} R_{[0][0]} & R_{[0][1]} & R_{[0][2]} \\ R_{[1][0]} & R_{[1][1]} & R_{[1][2]} \\ R_{[2][0]} & R_{[2][1]} & R_{[2][2]} \end{pmatrix} * \begin{pmatrix} x \\ y \\ z \end{pmatrix} + \begin{pmatrix} Tx \\ Ty \\ Tz \end{pmatrix} \tag{4}$$

d) Bi – 3xN matrix representing the unit quaternion of the Kinect global 3D point

e) Ai – 3xN matrix representing the unit quaternion of the Kinect local 3D point

f) s – Scale factor if needed (default 1)

To obtain the transformation matrix and calibrate one Kinect skeleton to K0 skeleton, at least four joints must be detected by the two calibrating Kinect at the same time. It was assumed that captured skeleton data is reliable when the person is standing in front of the sensor and two Kinects can track all 20 joints at the same time in a static trial. To get the more accurate transformation matrix, 120 frames of reliable skeleton data are captured. The sum of the 20 joints coordinate difference values between calibrated Kinect and KO is calculated as per (5).

$$CDV_i = \sum_{j=0}^{20} \left(\begin{bmatrix} A_j.x \\ A_j.y \\ A_j.z \\ 1 \end{bmatrix} - M_{AB} * \begin{bmatrix} B.x \\ B_j.y \\ B.z \\ 1 \end{bmatrix} \right), (i = 0, \dots, 119) \quad (5)$$

By comparing 120 sums of the coordinate difference values, the transformation matrix with minimum coordinate difference sum is chosen. Note that because the sampling frequency of the multi Kinect system is 35Hz, an oversampling was completed to synchronize the gait system with the other modules of the system. This synchronization was achieved by the Kinect server. The server ensured the packets for each Kinect arrived simultaneously to ensure synchronization.

3.4.1.1 The Multi Kinect Skeleton Fusion

Each Kinect skeleton contains 20 3D joints. The Kinect SDK provides the joint tracking state of every joint and it is important in this study to determine each transformation matrix. This property has three values: "*Tracked*", "*Inferred*", and "*NotTracked*". "Tracked" indicates that the joint is detected by the depth frame. "Inferred" indicates the joint is not being captured by the depth frame but there is a calculation to determine the joint. "NotTracked" indicates that the joint position is indeterminable. This led to calculating the skeleton confidence (SC) when generating the transformation matrixes as in (6). This property is used to filter unreliable data (Skeletons with many "Inferred" and "NotTracked" joints) from Multi Kinects.

$$SC_k = \sum_{j=0}^{19} JS_j, (k = 0, \dots, 3;\ j = 0, \dots, 19) \quad (6)$$

j) SC_k – The skeleton confidence from the k^{th} Kinect

k) JS_j – The j^{th} joint tracking state (1 if "Tracked", else 0)

A single Kinect is ideal to track a user from a frontal side. Hence, for the back-side detection, the Kinect SDK still captures the user as a frontal view, capturing a noncurated skeleton. Based on the SC, 2 points were reduced for the SC calculation if it is a "back" Kinect (K2) as in (7).

$$SC_k = \begin{cases} SC_k - 2, \ if \ \ k^{th} = K2 \text{ "back"} \\ SC_k, \qquad\qquad\qquad\qquad else \end{cases}, \ (k = 0, \dots, 3) \tag{7}$$

Due to this limitation, not all Kinects can track a reliable skeleton of the user and the most reliable skeleton is selected as main skeleton. For being the “main” Kinect, K0 has the highest priority, followed by K1, K3, and K2.

Each 2 adjacent Kinects are fused to generate a fused skeleton. The joint weight of each joint of two Kinects are then calculated. To calculate the joint weights, each skeleton confidence and tracking states of both skeletons are combined as in (8) and based on the joint weight, smoother fused skeletons are generated as per (9). The final fused skeleton is composed of all joints of the smoother skeletons.

$$JW_{kj} = \begin{cases} SC_k, \ if \ \ \mathrm{JS}_j = \text{"Tracked"} \\ SC_k/2, \qquad\qquad\qquad else \end{cases} \tag{8}$$

c) SC_k – The skeleton confidence from the k^{th} Kinect

d) JS_j – The j^{th} joint tracking state (1 if “Tracked”, else 0)

$$\overrightarrow{\mathrm{SJ}}_\mathrm{j} = \frac{\mathrm{JW_{1j}}.\overrightarrow{\mathrm{TAS}}_\mathrm{1j} + \mathrm{JW_{2j}}.\overrightarrow{\mathrm{TAS}}_\mathrm{2j}}{\mathrm{JW_{1j}} + \mathrm{JW_{2j}}} \tag{9}$$

e) $\overrightarrow{\mathrm{SJ}}_\mathrm{j}$ – The j^{th} smoothed joint coordinate vector

f) JW_1 and JW_2 – The j^{th} joint weights of the two adjacent Kinects

g) $\overrightarrow{\mathrm{TAS}}_\mathrm{1j}$ and $\overrightarrow{\mathrm{TAS}}_\mathrm{2j}$ – The j^{th} joint’s coordinate vectors of the two adjacent Kinects

3.4.2 Inertial Measurement Unit Module

The IMU module contains 4 IMU sensors. A real-time wireless synchronization and streaming protocol for multiple IMU needed to be designed and developed. The developed protocol fuses, in real-time, accelerometer, gyroscope, and magnetometer data and generates the quaternion orientation. The data is synchronized with the computer CPU clock ensuring no data is lost.

A MATLAB script for the multi IMU streaming was developed to perform the following capture protocol: sampling frequency of all sensors was defined to be 51.2Hz to avoid sensor drifting; internal configuration of each IMU; synchronization between the sensors; and, start/stop IMU system data capture. More specifically in terms of internal configuration of each IMU, 10 streams of data were available and captured: 3D acceleration from accelerometer (Accxyz), 3D angular velocity from gyroscope (Gyroxyz), 3D magnetic field from a magnetometer (Magxyz), and a timestamp [151]. As discussed later in this section, the Accxyz, Gyroxyz, Magxyz, were fused to provide quaternion representation. Each IMU has enough internal memory to store sessions but each of the sensors has its own time clock. Hence, synchronization of all 4 IMU during data capture is required. An algorithm was designed and implemented to achieve synchronization. Pseudo code for this algorithm is provided in Algorithm 1.

Algorithm 1: Real-time Multi Shimmer Streamer

```
function MultiShimmer(comPorts, jointNames, captureTime)
Input: 4 com Ports (one for each IMU), joint names, and capture time
Output: The .csv files containing each IMU data
        if all sensors are connected through BT protocol then
            Define Shimmer Handle Class instance;
            Define sample rate;
            Set internal board to 9DOF;
            Enable Shimmer internal sensors (Acc, Gyro, Mag);
            Synchronize sensor clock with PC
            if IMUs are ready to capture then
                Start assessment and capture
                Audio alert
            while elapsedTime < captureTime do
                Write data in CVS file
                IMU quaternion sensor fusion
            end while
            Stop assessment and capture
            Audio alert
            Write the percentage of packets to detect any lost information
        end
        Disconnect Shimmers
    end
end
```

[Algorithm 1. The function receives COM ports, joint names and capture time and generates synchronized and calibrated sensor data. The function also generates quaternions for Euler angle calculation]

To represent orientation of a rigid body or frame coordinates in 3D space, a quaternion representation was employed. This complex number representation can define any spatial rotation around a fixed point or coordinate system. A quaternion $q = [q_0\ q_1\ q_2\ q_3]$, can be used to get an angle θ about a fixed Euler axis [49] and (10). To get the angle between two joints, quaternion matrixes were obtained by the fusion of the 3 IMU internal modules (Accxyz, Gyroxyz, Magxyz,) using a Madgwick-based orientation filter [148].

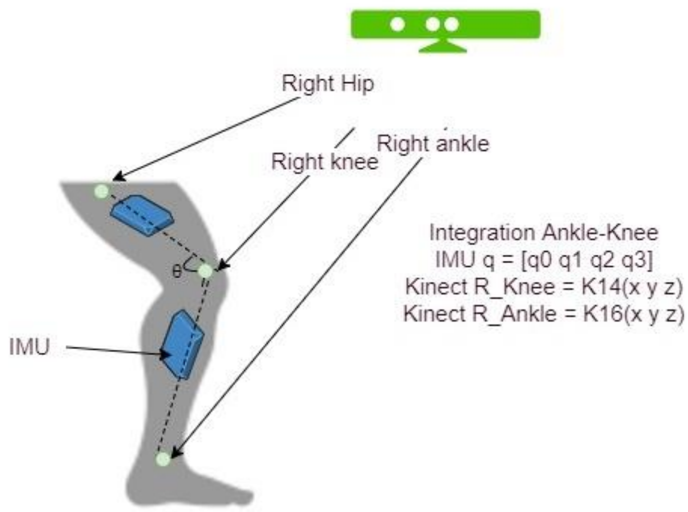


Figure 23. Kinect joints and IMU quaternion for integration.

The quaternion generated by the function can represent spatial rotation of each sensor and represents angles in each axis. Having each Euler angle, it is then possible to reference one IMU to another and get the angle between two sensors. The angle between two IMUs was used as part of the walking evaluation during experiments. The integration of the multi Kinect skeleton and IMU Modules was achieved by combining unit quaternions from 2 Kinect joints K_{xyz} and quaternions from the IMU located in the mid-point of those 2 joints q = [q_0 q_1 q_2 q_3] by rotating the quaternion q around vector v directing the two Kinect joints (v = K1 - K2) as in (11) and Fig. 23. After getting the angles of IMU and Kinect, the angles are merged, and a combined output is generated.

$$\begin{bmatrix}\phi \\ \theta \\ \Psi\end{bmatrix} = \begin{bmatrix} \arctan\frac{2(q_0\, q_1 + q_2\, q_3)}{1-2(q_1^2+q_2^2)} \\ \arcsin\left(2(q_0\, q_2 - q_3\, q_1)\right) \\ arctan\frac{2(q_0\, q_3 + q_1\, q_2)}{1-2(q_2^2+q_3^2)} \end{bmatrix} \tag{10}$$

$$\phi - rotation\ about\ the\ x\ axis$$
$$\theta - rotation\ about\ the\ y\ axis$$
$$\Psi - rotation\ about\ the\ z\ axis$$

$$v' = \begin{bmatrix} v'_1 \\ v'_2 \\ v'_3 \end{bmatrix} \begin{bmatrix} (1-2q_2^2-2q_3^2) & 2(q_1q_2 \ +q_0\,q_3) & 2(q_1q_3 \ -q_0\,q_2) \\ 2(q_1q_2 \ -q_0\,q_3) & (1-2q_1^2-2q_3^2) & 2(q_2q_3 \ +q_0\,q_1) \\ 2(q_1q_3 \ +q_0\,q_2) & 2(q_2q_3 \ -q_0\,q_1) & (1-2q_1^2-2q_2^2) \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix} \tag{11}$$

3.5 Experimental Protocol

The experimental protocol adheres to the approach taken in numerous related works in the literature [152-154] and included a number of steps:

a) Participant recruitment.

b) Information sheet and consent form (Appendix A and B).

c) Plug-in gait marker placement for VICON system (Appendix C).

d) Joint measurements for VICON system (Appendix D).

e) 12 trials per participant (1 calibration and walks).

10 healthy participants completed 12 trials each, providing a total of 96 individual datasets. During each trial, motion data was captured using the multimodal system and VICON simultaneously, hence allowing direct comparison.

Before the experiment, an information sheet was given to each participant to explain the experiment, purpose of the project, and data confidentiality procedures. The participant was also required to sign a consent form. As part of the set-up stage of the experiment, reflective markers were placed on the body with double sided tape following the Plug-In-Gait methodology from VICON [155]. Each marker placement and measurement took approximately 45 minutes. After mark placement, joint measurements were taken to provide additional data on each participant. This measurement was taken in the following body segments: arms, legs, height, hip, and shoulders. Finally, the 4 Shimmer IMUs were attached to the participant's body using elastic straps. The sensors were placed at mid-points of chest, sacrum, thigh, and tibia (Fig. 24) [156].

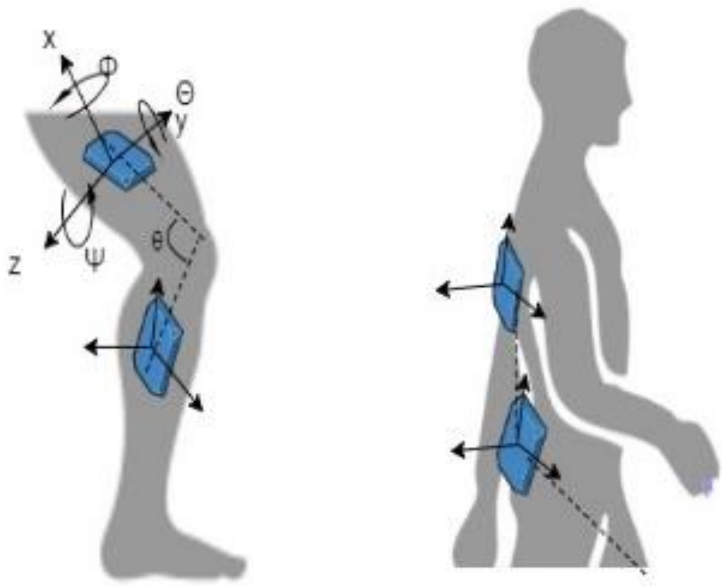


Figure 24. IMU leg sensor placement. The sensors were placed at mid-points of chest, sacrum, thigh, and tibia.

A single trial was achieved when the participant completed a full gait cycle 0-100% (Fig. 1) towards the frontal Kinect. This cycle happens when the participant steps on the ground (heel strike), removes the heel stepping with the other foot (initial swing), and steps on the ground with the same foot in heel strike (terminal swing) [22].

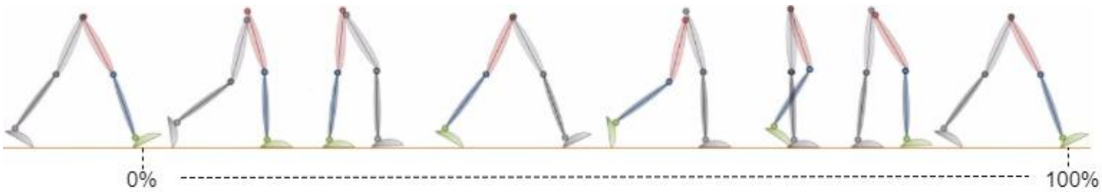


Figure 1. Gait cycle (Same as in Chapter 2)

The three streams of data (Kinects, IMU, and VICON) were normalized and synchronized showing a gait cycle. Before data collection, static trials were performed to calibrate the Multi Kinect system, the IMUs, and VICON system as per Fig. 25.

Figure 25. Static trials. These trials calibrated all streams of data: Vicon and gait system. Raw data from each sensor was also saved for all trials.

3.6 Data and Signal Processing

3 distinct datasets were captured for each user in each trial: Multi Kinect, Shimmer, and VICON. The Multi Kinect dataset of 5 skeletons (4 single Kinect Skeletons and 1 fused Kinect Skeleton) was stored in a .csv file and each skeleton were composed of 20 joint points. Data from Shimmer IMU was stored in a matrix format as described in Section 3.4. The VICON dataset, like Kinect, was in 3D position format, and was captured (VICONxyz) on a per reflective marker basis. During each trial, some of the markers were occluded (a known problem with VICON). Hence, post-test, each VICON trial needed to be processed separately, frame per frame, to ensure all gaps were filled using spline fill and pattern fill gap filling operations [157].

To compare VICON and each Kinect three tasks needed to be completed: (1) select Kinect joints that can be related to VICON reflective markers (e.g. same body segment; right arm, right leg, hip; (2) change VICON local coordinate system into Kinect global coordinate system; and, (3) synchronize both systems with an external event. For (3), a jump on a force plate was used and this event captured by the force plate generated a trigger for the systems.

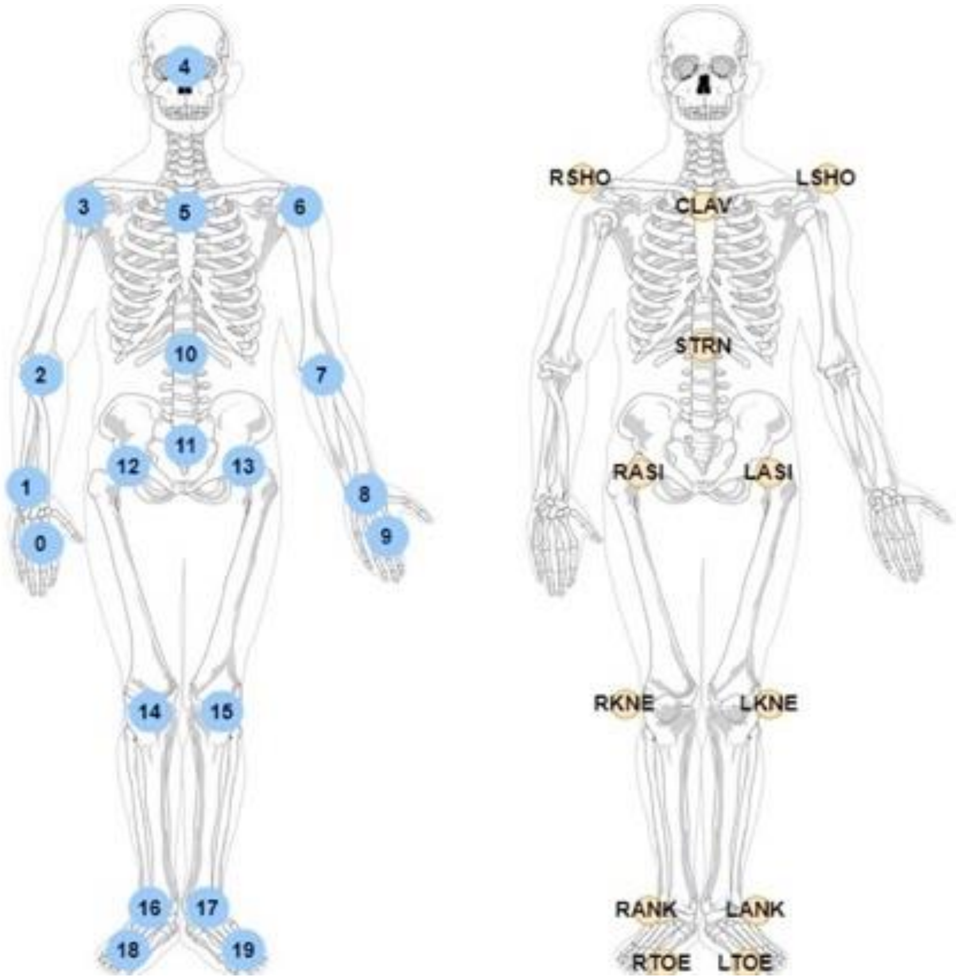


Figure 26. (a) Kinect joint index, (b) VICON Plug-in-gait marker placement

As per Fig. 26, 12 joints were selected via the Plugin GAIT and were compared with respective Kinect joints. These were: right shoulder (3, RSHO), shoulder centre (5, CLAV), left shoulder (6, LSHO), spine (10, STRN), right hip (12, RASI), left hip (13, LASI), right knee (14, RKNE), left knee (15, LKNE), right ankle (16, RANK), left ankle (17, LANK), right foot (18, RTOE), and left foot (19, LTOE); all of which are important for GAIT variable extraction and analysis. Fig. 27 shows that there is a difference between VICON markers and Kinect joint. This difference is explained because each marker is attached onto skin whilst Kinect joints are inferred in the anatomic position for the joint. However, this difference is not considered for joint signal comparison, and it was filtered during calibration procedure.

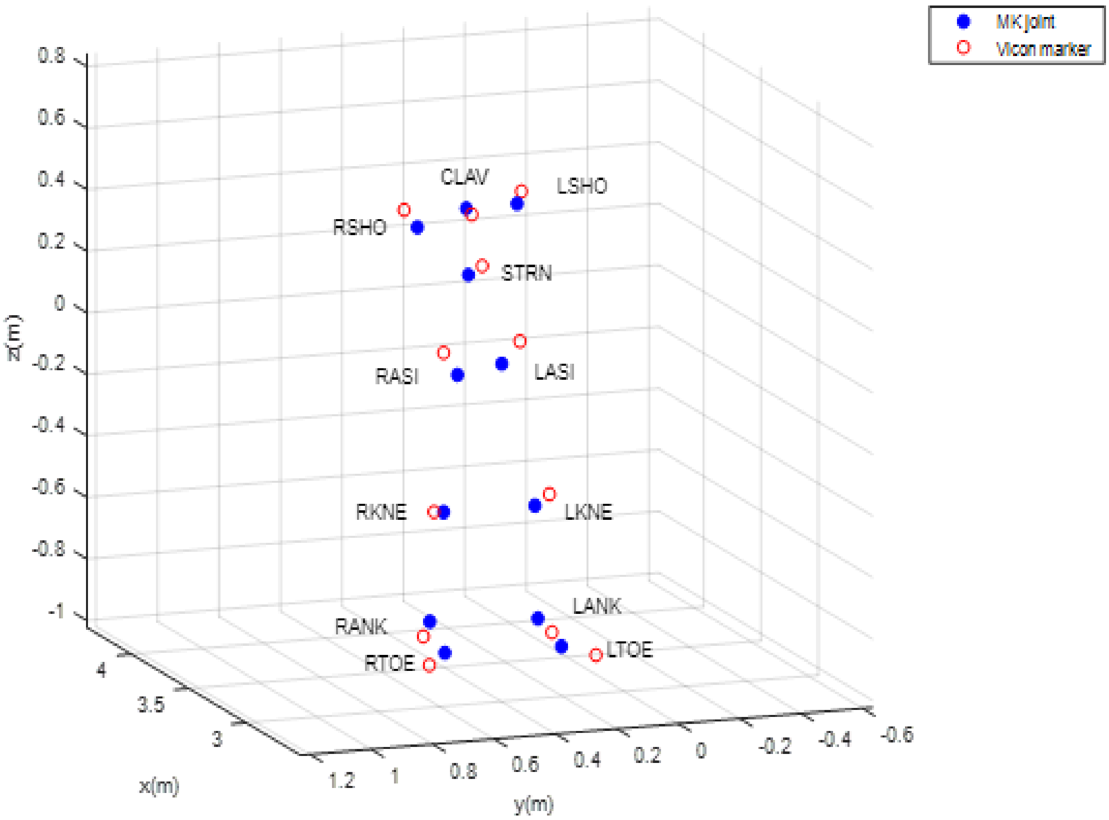


Figure 27. 3D plot of VICON and Multi Kinect points. Each VICON point is captured by an external marker onto skin. The Kinect joint is inferred by the real 3D anatomic position

It is possible to develop comparison methods using Cross-correlation for each single Kinect and Multi Kinect with VICON. The Cross-correlation is the similarity measurement of two signals with the displacement of one relative to other. This correlation has many uses like pattern recognition and signal displacement [158]. Considering each joint point in space (Kinectxyz and VICONxyz) as 3 distinct signals, the correlation of the signal can be evaluated. For the gait system, Principal Component Analysis (PCA) was applied. PCA is the statistic method to orthogonally convert a set of observations of possibly correlated variables into linear observations called Principal Components [159].

3.6.1 Gait Prediction and Confidence Bands

Hip and knee angles were evaluated as these joints are weight-bearing joints and most susceptible to require bone surgical interventions [160-162]. To evaluate angles from all data sets, two approaches were required: first, having three distinct points in space and second the quaternion function and Euler angles from two IMU. The angle between 3 points is equivalent of the angle between two vectors defined by the same 3 points.

Gait analysis often utilizes continuous curves to evaluate a full gait cycle. The cycle happens when the participant steps on the ground (foot strike), removes the heel stepping with other foot (initial swing), and step on the ground with the same foot in foot strike (terminal swing) [163]. Gait angle data is not composed of single points and cannot be statistically evaluated using common statistical analysis [164]. When dealing with single observations of data, prediction intervals are made for a probability interval. For continuous data, the analogous prediction contains a new prediction every time a new curve is added from population [165]. This method is called bootstrap and can give prediction intervals for gait curves at any confidence interval [166].

3.6.2 Spatiotemporal Variables

To evaluate the gait system, in addition to gait graphs, it is also important to evaluate spatial variables like gait and stride length, and temporal variables such as gait cycle time, stride times, and velocity. For those variables, an analysis of spatiotemporal variables of walk was performed. All variables of gait were also compared with the VICON system.

3.7 Results and Discussion

To evaluate the gait system, analysis on the cross-correlation of VICON and each Kinect, and principal components analysis of VICON with the gait system were performed. The results are presented in the following sections.

3.7.1 Differences in 3D space per joint and Cross-correlation

Table 1 displays the difference in 3-dimensional space between the Multi Kinect system joint locations and the VICON system. The mean difference of joint locations was found to be 3.10 cm for all joints in all trials (literature states differences from 0.3-10cm). When a VICON and Kinect signal differ, it is possible to measure the similarity using cross-correlation. The results of this cross-correlation are presented in Table 2.

Table 1. Joint location difference in cm: VICON and Multi Kinect comparison.

Joints/differences in cm					
RSHO	CLAV	LSHO	STRN	RASI	LASI
8.70	8.70	0.15	1.12	1.81	0.98
LKNE	LKNE	RANK	LANK	RTOE	LTOE
2.58	2.58	0.33	2.31	3.92	3.92

The Cross-correlation between VICON and Kinect shows that the frontal Kinect (K0) and the Multi Kinect (MK) have better results for cross-correlation 0.86 and 0.85 than the other combinations as expected (Table 2). The results for VICON and Kinects can be explained because the walking motion was performed towards the K0 and the sensor was programmed in a manner such that the best capture occurs when user faces the device. However, a single Kinect is not enough for a full 360º capture. Considering that the Multi Kinect skeleton is formed by the fusion of lateral and posterior Kinects (K1, K2, and K3), the Multi Kinect could maintain a stable joint correlation (0.85). The results for cross-correlation for Kinects 1, 2, and 3 have demonstrated that the correlation of each Kinect compared against VICON depends on which Kinect the participant is facing. This problem is overcome with a 3D multi Kinect in use.

Table 2. Cross-correlation per joint

Joint	K0	K1	K2	K3	MK
RSHO	0.98	0.58	-0.39	0.44	0.98
CLAV	0.74	0.41	-0.34	0.26	0.74
LSHO	0.98	0.60	-0.44	0.45	0.98
STRN	0.97	0.51	-0.37	0.34	0.97
RASI	0.95	0.36	-0.26	0.18	0.95
LASI	0.94	0.39	-0.29	0.16	0.94
RKNE	0.82	0.35	-0.11	0.09	0.85
LKNE	0.80	0.08	-0.14	0.12	0.81
RANK	0.82	0.36	-0.19	0.47	0.76
LANK	0.89	0.21	-0.11	0.34	0.84
RTOE	0.60	0.28	-0.18	0.39	0.64
LTOE	0.80	0.19	-0.09	0.33	0.78
Mean	0.86	0.36	-0.24	0.30	0.85

3.7.2 Knee and Hip angles

Hip and knee angles were evaluated as these joints are weight-bearing joints and most susceptible to require bone surgical interventions [167]. To evaluate angles from all data sets, two approaches were used: first, having three distinct points in space and second: from the quaternion function and Euler angles from two IMU. The angle between 3 points is equivalent of the angle between two vectors defined by same 3 points (12-14). Considering 3 points P1, P2, and P3 and vectors u and v:

$$u = P1 - P2 \text{ and } v = P3 - P2 \tag{12}$$

$$\cos\theta = \frac{u.v}{|u||v|} \tag{13}$$

$$\theta = arcos\left(\frac{u.v}{|u||v|}\right) \tag{14}$$

Figures 28 and 29 show VICON, IMU, and gait system knee flexion angles in a gait cycle. Figures 30 and 31 show the same type of graph for hip flexion angles. The main areas of difference are highlighted in red: where the results exceed one standard deviation from VICON. From the figures presented, the x axis shows the percentages of gait from 0 to 100%. The initial phase 0% happens when the heel contacts the ground and 100% when the same heel contacts the ground. The y axis represents flexion angles of hip and knee. The grey curve reflects one standard deviation from Vicon. From these graphs, visual representation of the gait cycle graphs of IMU, gait system and VICON can be visualized. From the visual perspective, the IMU itself and the integration of IMUs with Kinects provides better angle representation (Fig 28b and Fig. 29, Fig. 30b, and Fig. 31).

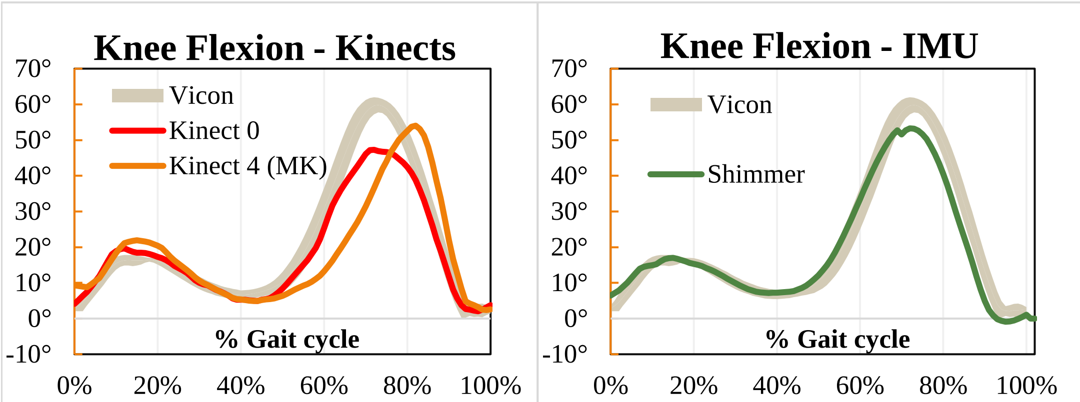


Figure 29. Vicon vs. Kinects and Vicon vs. IMU (Shimmer) for knee flexion angles.

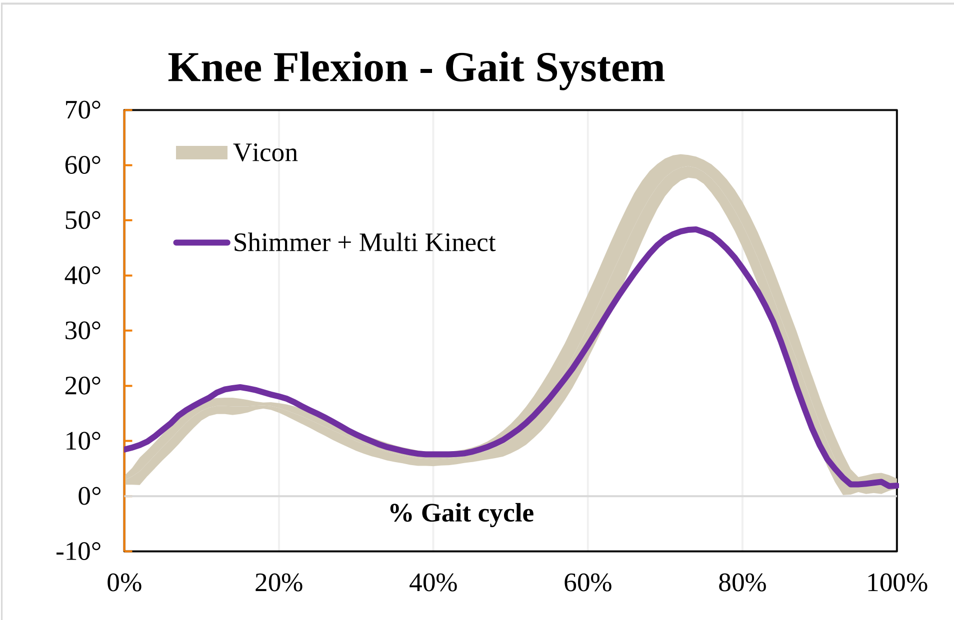


Figure 28. Vicon vs. Gait System for knee Flexion angles

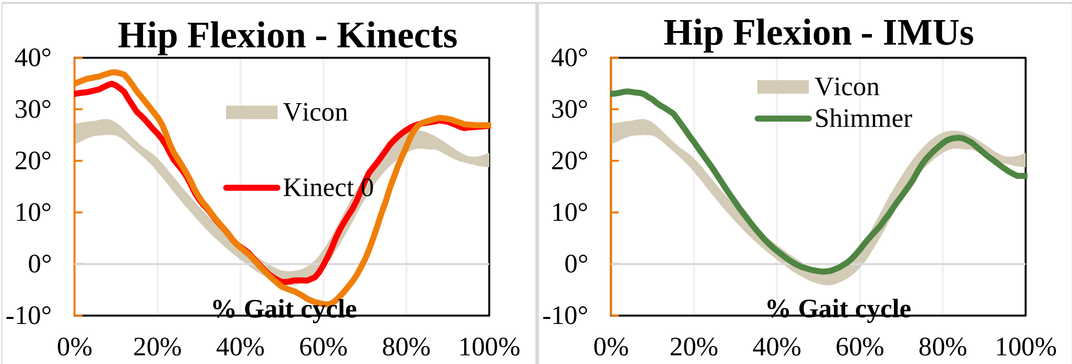


Figure 30. Vicon vs. Kinects and Vicon vs. IMU (Shimmer) for hip flexion angles

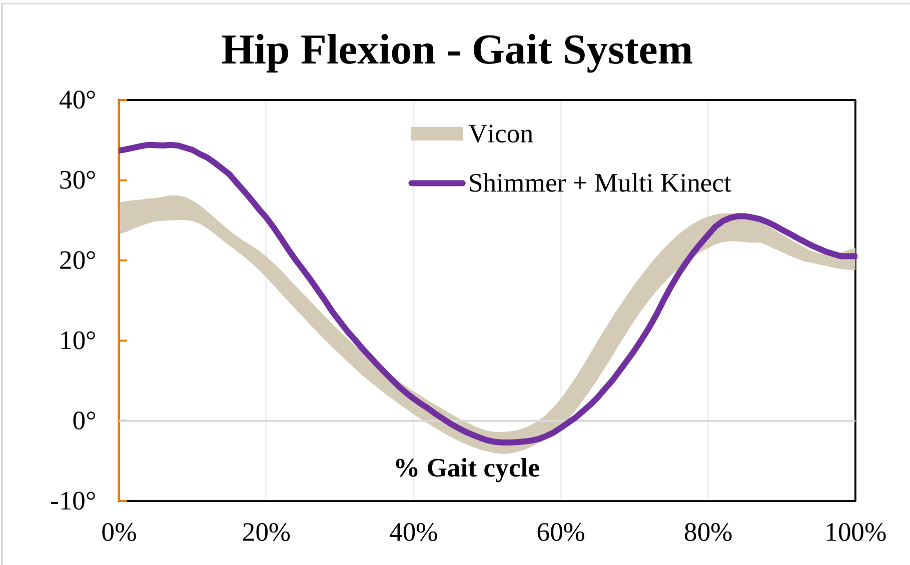


Figure 31 - Vicon vs. Gait System for hip flexion angles

To ensure similarities between the VICON and the other systems (Kinect frontal “K_0”, Multi Kinect, Shimmer, and gait system) are evaluated, statistical analysis was performed. Principal Component Analysis (PCA) was employed as it can extract the main components of variance and correlation. KMO & Bartlett’s Test of Sphericity [168] was employed as it is a measure of sampling adequacy of the data for component analysis for knee and hip angles. The KMO value must be above 0.6. and the sigma value less than 0.05%. The KMO value for knee and hip angles were 0.714 and 0.657, respectively, and sigma values of 0.02% and 0.03% were observed. These values assure PCA suits the data analysed [31].

3.7.2.1 **PCA in knee flexion.**

PCA was employed to determine (via variance), how many components could be used in the analysis. The total Eigenvalue must be above 1 in order to have a valid component. Eigenvalues of two main components of knee flexion groups were 5.34 and 1.4 and only components 1 and 2 were used. Component 1 explained 69.68% of variance, and component 2 explained 15.89%. Table 3 shows similarity of systems based on component 1 and 2 for the knee flexion group. Two groups are similar when they have component analysis close to 1. Because of that, no similarity was found in: VICON with Kinect 0, Shimmer, and gait system (0.97, 0.96 and 0.97, respectively). These can help to explain the similarities found in the gait angle graphs

Table 3. Component matrix for knee flexion group

System	Component	
	1	2
VICON	1	0.01
Kinect 0	0.97	0.00
Kinect 1	-0.49	0.06
Kinect 2	-0.36	0.08
Kinect 3	0.71	-0.27
Multi Kinect	0.80	0.24
IMU	0.96	.127
Gait System	**0.97**	.194

3.7.2.2 **PCA in hip flexion.**

PCA was also employed to determine (via variance), how many components could be used in the analysis for hip angles. Eigeinvalues of two main components of hip flexion groups were 6.17 and 1.04. Components 1 and 2 are used. Component 1 explained 7.14% of variance, and component 2 explained 13.05%. Table 4 shows similarity of systems based on component 1 and 2. Similarity found in: VICON with gait system (0.98). These results indicate that only a single Kinect or an IMU would be enough to represent angles, but they do not represent the combined system. A single Kinect does not represent the full 3D body in 360o and an IMU does not give 3D points in space. The fact that IMU itself was capable of replicate hip angles with 0.99% for PCA, was an indicator that maybe IMUs alone are enough for some studies.

Table 4. Component matrix for hip flexion group

System	Components	
	1	2
VICON	1	0.19
Kinect 0	0.98	0.10
Kinect 1	-0.55	0.45
Kinect 2	-0.37	-0.10
Kinect 3	0.33	0.85
Multi Kinect	0.97	-0.19
IMU	0.99	-0.03
MM System	**0.98**	-0.02

3.7.3 Gait Prediction and Confidence Bands results

This section presents the 95% bootstrap prediction band of VICON compared with Multi Kinect, IMU, and gait system. The graphs in red represent the Multi Kinect and IMU outputs whereas the blue represents the gait System representation. The flexion angles are defined in full gait cycle. The area between two black curves represent the VICON prediction band. Any curve outside this area does not fit the VICON curve, hence it cannot be used to evaluate angles. From the figures presented, the x axis shows the percentages of gait from 0 to 100%. The initial phase 0% happens when the heel contacts the ground and 100% when the same heel contacts the ground. The y axis represents flexion angles of hip and knee.

For the Knee and Hip flexion curves from Multi Kinect module (Fig. 32), since there is a processing time in generating a fused skeleton, filtering noise, and calibrating coordinates, there is also a delay in outputting of gait graphs and might be an issue where applications demand precise timing information. The use of the MS Kinect in applications at higher speed (e.g. sprinting, fast movements, sports mechanics) is discouraged. The prediction band informs that for initial knee flexion angles (0^o - 20^o) and maximum flexion (60^o - 80^o degrees), the MK module was outside the prediction band and could not represent the VICON curve for all degrees. The hip flexion curve for the 60^o - 80^o angles is also outside the prediction band of VICON.

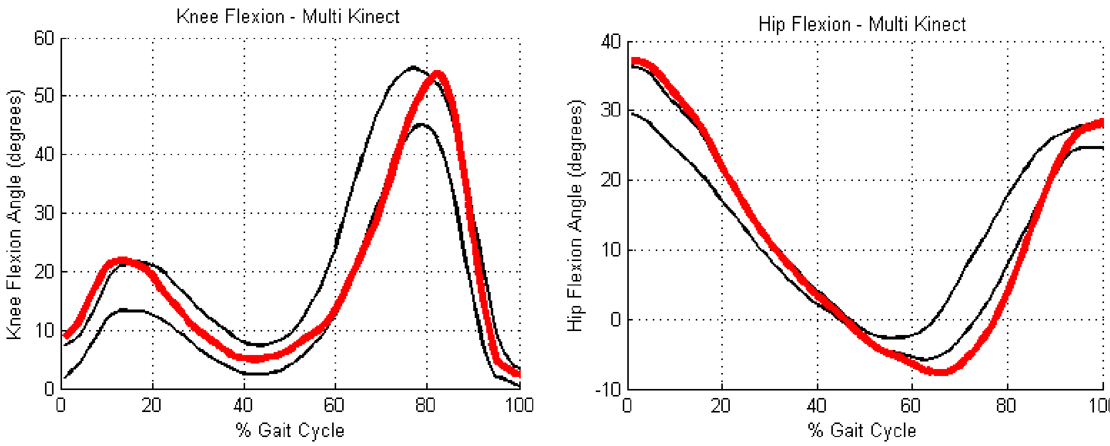


Figure 32. Knee and hip flexion angles from Multi Kinect module (red) and confidence bands of 95% from Vicon.

For the Knee and Hip flexion curves from IMU module (Fig. 33), there is no delay in outputting gait graphs. The IMUs can provide information at higher sample rates when compared with Kinect. Initial flexion angles from knee and hip are outside prediction band. The IMU module can represent gait graphs of hip and knee. However, they cannot represent 3D points and could not be used in applications where 3D and body representation are essential.

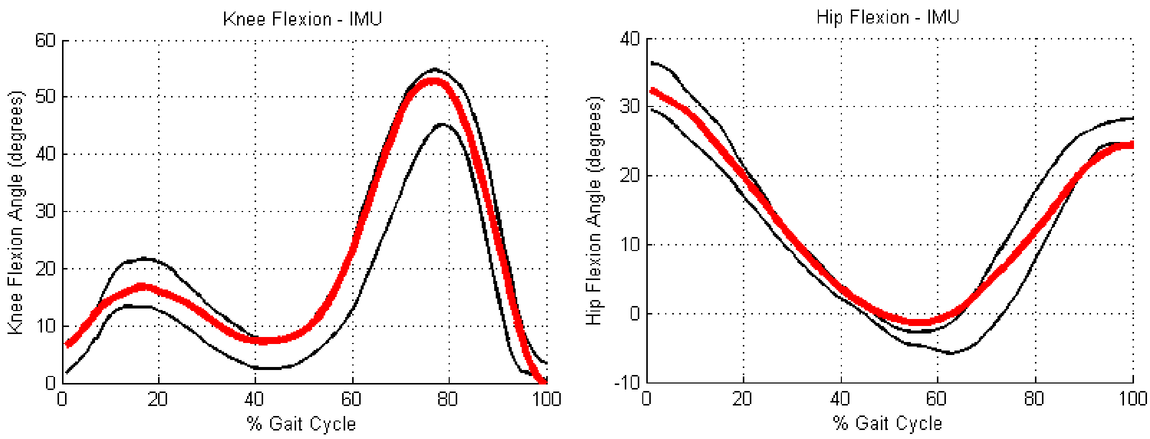


Figure 33. Knee and hip flexion angles from IMU module (red) and confidence bands of 95% from Vicon.

The proposed gait system by the combination of MK and IMU could provide knee and hip angles from gait as per Fig. 34. From these graphs, visual representation of the gait cycle graphs of the gait system are generated. The current analysis examined knee and hip angles as these are the main weight bearing joints related to human gait. Based on the 95% bootstrap prediction, the gait system is capable of replicating angles in the sagittal plane of knee and hip and kept the output within the prediction bands.

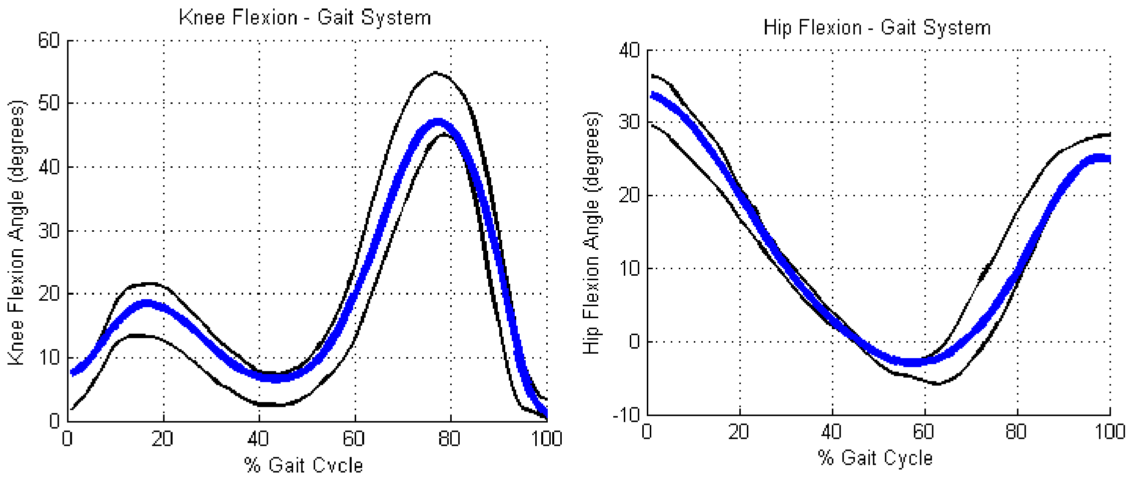


Figure 34. Knee flexion angles from gait system (blue) and confidence band of 95%.

Different analysis of gait angles across different modules of the system was published in previous chapter and [147]. Spatiotemporal analysis was also provided for a complete human gait analysis.

3.7.4 Spatiotemporal results

Table 5 shows results for spatiotemporal gait variables. This table compares VICON with the gait system. The results from the sigma value explains that there is no significant difference between two groups. Spatiotemporal units are defined; s = seconds, m = meters, m/s = meters per second of gait cycle. It includes statistic results for an independent t-test. Assuming equal variances, the results showed that both groups VICON and gait system are comparable, thus the system outputs similar values. Lower accuracy of the MS Kinect for some lower joints like ankles and toes were found. This could interfere on the capability of the system to provide gait length (r = 0.88). The highest correlation was for gait cycle time (r = 0.99), thus the system could constantly capture the human gait from all trials. Considering works in literature [54, 57, 69], the system presented in this chapter was capable of outputting spatiotemporal variables with higher correlation between gait system and VICON. The literature on [146], an impressive work on Multiple Kinects, which has not compared their results with a gold standard system, reported results of 0.97 for right stride length, 0.83 for left stride length, and 0.92 for gait time. The current study demonstrates correlations of 0.99 for gait time and 0.95 for right and left stride length, which was a positive result, superior to the above described literature.

Table 5. Spatiotemporal results – VICON vs. Gait System

Variable	Group	Mean	Sd	Sig (2-tailed)	Pearson's Correlation (r)
Gait Cycle (s)	VICON	1.308	0.037	0.714	0.996
	Gait System	1.300	0.036		
Right Stride (s)	VICON	0.709	0.022	0.390	0.956
	Gait System	0.700	0.014		
Left Stride (s)	VICON	0.598	0.025	0.901	0.908
	Gait System	0.600	0.029		
Gait length (m)	VICON	0.958	0.152	0.840	0.886
	Gait System	0.941	0.160		
Stride length (m)	VICON	0.585	0.046	0.087	0.950
	Gait System	0.535	0.053		
Velocity (m/s)	VICON	0.734	0.127	0.892	0.919
	Gait System	0.724	0.130		

3.8 Conclusion and considerations for next study

The system presented in this chapter is a novel multimodal gait system, that combined a multiple Kinects module and inertial sensors module. The system performance was compared with the gold standard VICON system. This comparison included comparing VICON signals against all possible multi Kinect 3D Kinect skeleton composed of 4 physical Kinects and 1 generated 360^{o} multi Kinect skeleton. In addition, a comparison of VICON flexion-extension angles with the multi Kinect system and gait system (multi Kinect + IMU) was presented. The results have presented analysis and discussion on signals differences between the proposed system and VICON, as well as angles estimation differences from inertial sensors integration. The analysis has demonstrated the utility of the gait system (inclusive of its limitations). Based on this, many potential use cases of the gait system can be proposed. The system can promote angle estimation from the IMUs and position in space of multi Kinect. The proposed system is cheap; easy to set up; displays clear and easily interpretable results; is marker-less; supports 360 degrees of motion analysis; is portable; and does not require a large set up space or environment.

The analysis has demonstrated the utility of the gait system (inclusive of its limitations). Based on this, many potential use cases of the gait system can be proposed. Analysis and consideration of the results infers that the system was capable of replicating gait angles of Knee and Hip with 95% bootstrap confidence interval. Spatiotemporal results showed similarity with significant results of 99% on gait cycle time (s), 95% on right stride time (s), 90% on left stride time (s), 88% on gait length (m), 95% on stride length (m), and 91% on gait velocity (m/s).

A summary of capabilities of the gait system with other techniques described in this chapter is shown in Table 6. MoCap Technologies such as VICON have high levels of precision and accuracy, however, difficulties with set up, high cost, and the use of markers provided barriers for use in applications and fields. The system considers the use of IMUs as a form to enhance joint angles, it is marker-less which makes set up quick and easy, and provided accurate spatiotemporal gait variables. Applications of the multimodal gait system are beyond low-cost gait analysis, it includes rehabilitation feedback, and Virtual and Augmented Reality applications which are topics the next chapter.

Table 6. Technology comparison

Feature	Description	VICON	Multi-Kinect	IMU	Gait System
Marker-less	Use markers?	✗	✓	✗	✓
Portable	Lightweight sensors	✗	✓	✓	✓
360º View	Can be used in any view?	✓	✓	✓	✓
Quick set-up	Easy set-up	✗	✓	✓	✓
Low-cost	Final price.	✗	✓	✓	✓
Body frame	Can reproduce 3D body?	✓	✓	✗	✓
Temporal Gait	(e.g. time between steps)	✓	✓	✓	✓
Spatial Gait	(e.g. distance between steps)	✓	✓	✓	✓
Joint angles	(e.g. knee angle)	✓	✗	✓	✓

These results indicated that this gait system could be used for gait analysis. Considering the next steps of this project outlined in the introduction (gait feedback for varus/valgus feedback), it was decided that only IMUs would be enough for the intended feedback application.

Considering the hardware requirements for this project to address varus/valgus alignment, it was chosen an IMU that uses Wi-Fi instead of Bluetooth [169]. In this way, the range of the system would be increased, and the system would be even more portable.

Next chapter introduce an updated system utilizing only IMUs as a real-time immersive multimedia haptic/Augmented Reality feedback tool for gait analysis.

4 Study 1: QoE Evaluation of Haptic and AR feedback for varus/valgus

4.1 Study Aims

In the previous chapter, the design and evaluation of a system capable of providing gait variables was presented. The next part of the holistic gait feedback system is evaluating different feedback modalities. The study presented in this chapter aims to compare two feedback modalities: haptic and Augmented Reality (AR) in gait. The aim of the feedback is to reduce varus/valgus misalignments (see Section 4.4.3), which can cause serious orthopaedics problems such as osteoarthritis and injuries [25]. This chapter is an "explicit" post experience comparison of the two different types of feedback that considers 3 different types of post experience questionnaires (MOS, NASA-TLX, and SAM). The study also looks at subjective evaluation through questionnaires and assesses differences across gender.

4.2 Motivation

For issues identified through gait analysis, traditional rehabilitation approaches have relied on expert guided feedback in clinical settings. Such efforts require the presence of an expert to guide the re-training (to evaluate any improvement) and the patient to travel to the clinic. Nowadays, potential opportunities exist to employ the use of digitized "feedback" modalities to help a user to "understand" improved gait technique. This is important as clear and concise feedback that is easy to understand can enhance the quality of rehabilitation and recovery.

A critical requirement emerges to consider the "quality" of feedback from the user perspective i.e. how they process, understand and react to the feedback. In this context, this chapter reports results of a QoE evaluation of two feedback modalities: AR and Haptic employed as part of an overall gait analysis system.

The existing literature presents various feedback mechanisms that are used in many research works (discussed in the related work). However, novel immersive technologies such as AR) are emerging that potentially have utility. These current tools have been shown to have utility but as discussed in the literature review, they also have individual limitations which provide rationale for the current study. In order to test AR experience in gait feedback and to assess those limitations against state-of-the-art technologies, the QoE evaluation is necessary and it is the motivation of this study.

4.3 Study Overview

This chapter reports the results of a QoE evaluation of two feedback modalities: AR and Haptic employed as part of an overall gait analysis system. The aim of the feedback is to reduce varus/valgus misalignments. The QoE analysis reported in this chapter considers objective (improvement in knee alignment) and subjective (questionnaire responses) user metrics. 26 participants, as part of a within subject design, answered 3 different categories of questions. Firstly, they answered 12 questions on QoE aspects such as utility, usability, interaction, and immersion of the feedback modalities via post-test reporting. Other post-test questionnaires included NASA-TLX to assess cognitive workload, and SAM for assessment of emotion. In addition, for all participants, objective metrics of participant performance (changes in angles and alignment) were also considered as indicators of the utility of each feedback modality. From the developed questionnaire, the findings show statistically significant higher QoE ratings for AR feedback. In addition, the number of knee misalignments was reduced to a greater extent after users experienced AR feedback (35% improvement with AR feedback when compared to haptic, which had no significant improvement). Gender analysis showed significant differences in performance for number of misalignments and time to correct valgus misalignment for AR feedback for males. The female group self-reported higher utility and QoE ratings for AR when compared to the male group.

4.4 Gait Feedback System Design

The gait feedback system was fully designed in order to provide gait analysis and feedback. The gait system is composed of a capturing module, a presentation module and a data processing module and its design was informed from the studies and analysis presented in Chapter 3. The capturing module consists of 6 IMUs. The Feedback module contains two components: Haptic and Augmented Reality modules. Finally, the data processing system is a quadcore Intel Core i7 laptop, 16GB DDR4 RAM, 3.2Ghz, GTX 1060-6GB was used to integrate all modules and is also the Wi-Fi WebSocket server for all modules as per Fig. 35. In order to capture gait angles and knee alignment, the capturing module of IMUs was developed.

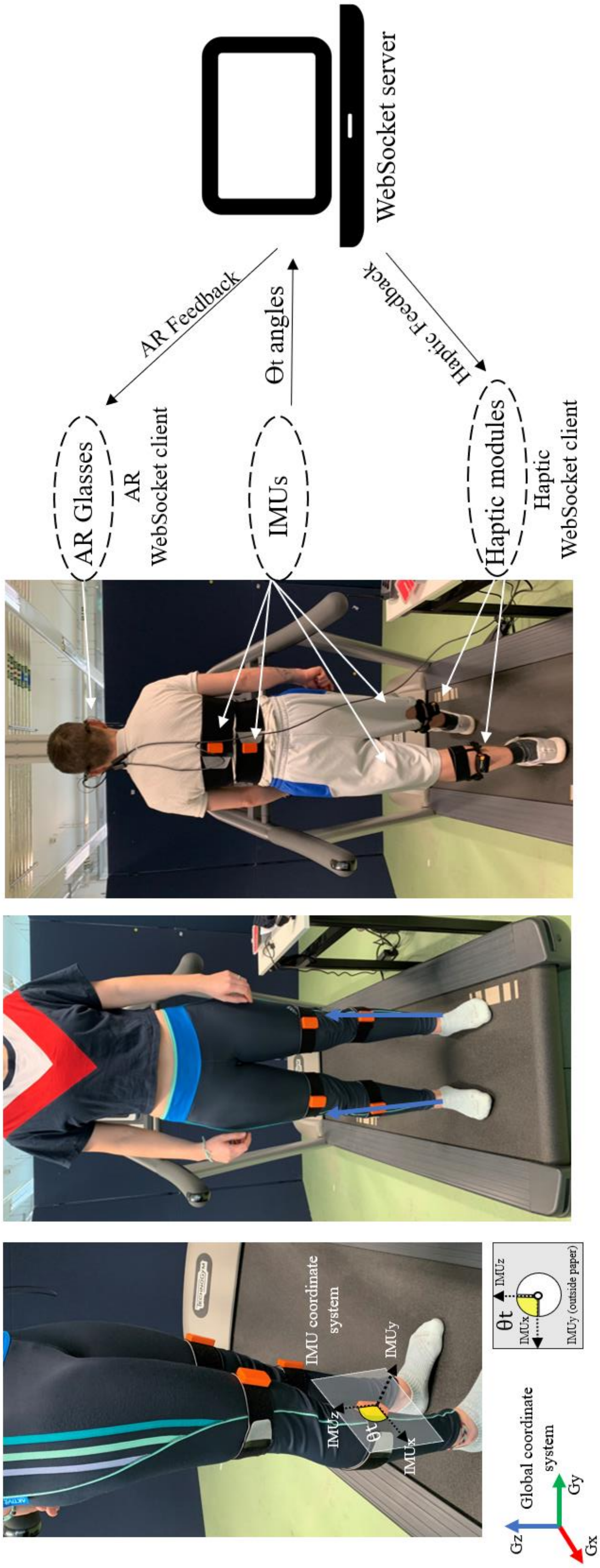


Figure 35. Gait feedback system modules and system architecture. The figure shows sensor placement and coordinate systems from different views.

4.4.1 Capturing Module – IMU

The capturing module contains 6 X-Sens IMU’s [169] and placed on the body at mid-points of chest, sacrum, thigh, and tibia as per Fig. 35. A real-time Wi-Fi protocol for multiple IMUs was developed in C#. Even though this sensor was from a different brand, the accuracy and setup were the same as the previous study. The only difference was from a capturing perspective, where the X-Sens IMU allows Wi-Fi interfaces. This protocol was responsible for both data streaming and synchronization. This protocol is important as it ensures that no data is lost, that feedback is presented without delay, and that all modules can work independently. In terms of internal configuration of each IMU, 10 streams of data were captured: 3D acceleration from triaxial accelerometer (Acc_{xyz}), 3D angular velocity from triaxial gyroscope ($Gyro_{xyz}$), 3D magnetic field from a triaxial magnetometer (Mag_{xyz}), and UNIX timestamp. As discussed later in this section, the internal sensors were fused, in real time, to provide a quaternion representation. The datasets from the IMU’s were synchronized with the computer CPU clock ensuring minimum packet loss. This capturing module processes in real time quaternion and Euler angles of each sensor and generates angles for knees, hips, tibia, and trunk lean in any 3D plane. Data from the sensors was sampled at 40Hz on all three axes and sent through a Wi-Fi interface to the server computer. The updated algorithm for Euler angles is a novel contribution of this work. There was no other research to date that reported 3D angle generation from quaternion and Euler angle integration [122, 170].

To represent the orientation of a rigid body, or frame coordinates in 3D space, a quaternion representation was employed. This complex number representation defines any spatial rotation around a fixed point or coordinate system. A quaternion $q = [q_0\ q_1\ q_2\ q_3]$ was used to calculate an angle θ about a fixed Euler axis [156, 171]. To get the angle between two joints with IMU, quaternion matrixes were obtained by fusion of the 3 internal modules (Acc_{xyz}, $Gyro_{xyz}$, Mag_{xyz}) using a Madgwick-based orientation filter [148].

The quaternion generated by the orientation filter represents the spatial rotation of each IMU and can generate any joint angle (knee angle in this case) for each axis. Having each Euler angle, it is then possible to reference one IMU to another and determine the angle between two sensors. This angle between the two IMU's was used as part of the walking evaluation during experiments.

At the start of each test, while the user was standing sensor calibration was obtained using the IMU quaternion in Euler angles (θ_x, θ_y, and θ_z) in North-East-Down (NED) ZYX sequence as in (15).

$$\begin{bmatrix} \theta_x \\ \theta_y \\ \theta_z \end{bmatrix} = \begin{bmatrix} \arctan \frac{2(q_0 q_1 + q_2 q_3)}{1-2(q_1^2+q_2^2)} \\ \arcsin\left(2(q_0 q_2 - q_3 q_1)\right) \\ arctan \frac{2(q_0 q_3 + q_1 q_2)}{1-2(q_2^2+q_3^2)} \end{bmatrix} \tag{15}$$

To find the tibia projection angle in the frontal, lateral, and sagittal planes, unit vectors on each quaternion coordinate system need to be calculated. This calculation converts the current quaternion of each IMU to direction cosine matrices. The calibrated $\theta_x, \theta_y, \theta_z$ is converted into a unit vector in the ZYX order as in (16).

$$\begin{bmatrix} \mathrm{IMU}_x \\ IMU_y \\ \mathrm{IMU}_z \end{bmatrix} = \begin{bmatrix} Cos(\theta_y)Cos(\theta_z) & -Cos(\theta_y)Sin(\theta_z) \\ Cos(\theta_z)Sin(\theta_x)Sin(\theta_y) + Cos(\theta_x)Sin(\theta_z) & Cos(\theta_x)Cos(\theta_z) - Sin(\theta_x)Sin(\theta_y)Sin(\theta_z)\ldots \\ -Sin(\theta_x) & Cos(\theta_y)Sin(\theta_x) \end{bmatrix}$$

$$\begin{matrix} Sin(\theta_z) \\ \ldots -Cos(\theta_y)Sin(\theta_x) + Cos(\theta_x)Sin(\theta_y)Sin(\theta_z) \\ Cos(\theta_x)Cos(y) \end{matrix}\Bigg] \tag{16}$$

This equation is then applied to calibrated Euler angles. To get any IMU angle, each IMU quaternion is converted to a Direction Cosine Matrix (DCM) (17) and multiplied by the direction vector IMU = (IMU_x, IMU_y, IMU_z) as in (18). Finally, a trivial solution of a right-angle triangle of IMU_x, IMU_y, IMU_z on the directional vector (v) is applied to get angle at the desired plane (19). The angle θ between two IMU will be as in (20). The simplified algorithm is also presented in Appendix E

$$DCM = \begin{bmatrix} (q_0^2 + q_1^2 - q_2^2 - q_3^2) & 2(q_1 q_2 + q_0 q_3) & 2(q_1 q_3 - q_0 q_2) \\ 2(q_1 q_2 - q_0 q_3) & (q_0^2 - q_1^2 + q_2^2 - q_3^2) & 2(q_2 q_3 + q_0 q_1) \\ 2(q_1 q_3 + q_0 q_2) & 2(q_2 q_3 - q_0 q_1) & (q_0^2 - q_1^2 - q_2^2 + q_3^2) \end{bmatrix} \tag{17}$$

$$\begin{bmatrix} v_x \\ v_y \\ v_z \end{bmatrix} = [DCM] \begin{bmatrix} \mathrm{IMU}_x \\ IMU_y \\ \mathrm{IMU}_z \end{bmatrix} \tag{18}$$

$$\theta_{IMU} = \operatorname{atan}\left(\frac{v_x}{v_z}\right) \tag{19}$$

$$\theta = \theta_{IMU1} - \theta_{IMU2} \tag{20}$$

The real-time angle and feedback output from the system is shown as per Fig. 36. This output showed gait angles and a feedback control, which will be discussed in the next section.

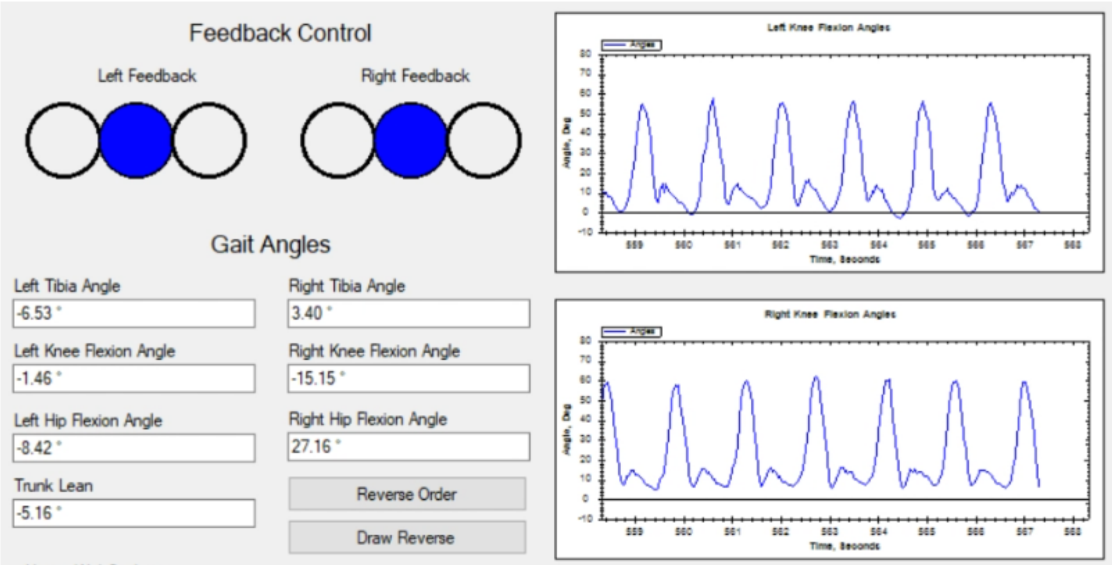


Figure 36. Angle output from Gat feedback system

4.4.2 Feedback Modules

In this section, Haptic and AR feedback modules are presented.

4.4.2.1 **Haptic Module**

A bespoke wearable haptic module was designed and manufactured for gait feedback purposes as illustrated in Fig. 40. The design and manufacture of this module was done as part of the PhD contribution. As per related works section, no off-the-shelf haptic modules satisfied the requirements of being lightweight, wearable, and provide a haptic sensation. The Haptic module was developed to provide the correct feedback to the user according to his/her movements [77]. The two haptic modules had an ESP8266 Wi-Fi microcontroller board with a WebSocket client. Each module was composed of a leg mounted strap; two vibration units (Fig. 40a); and a communication and microcontroller module with battery unit (Fig. 40b).

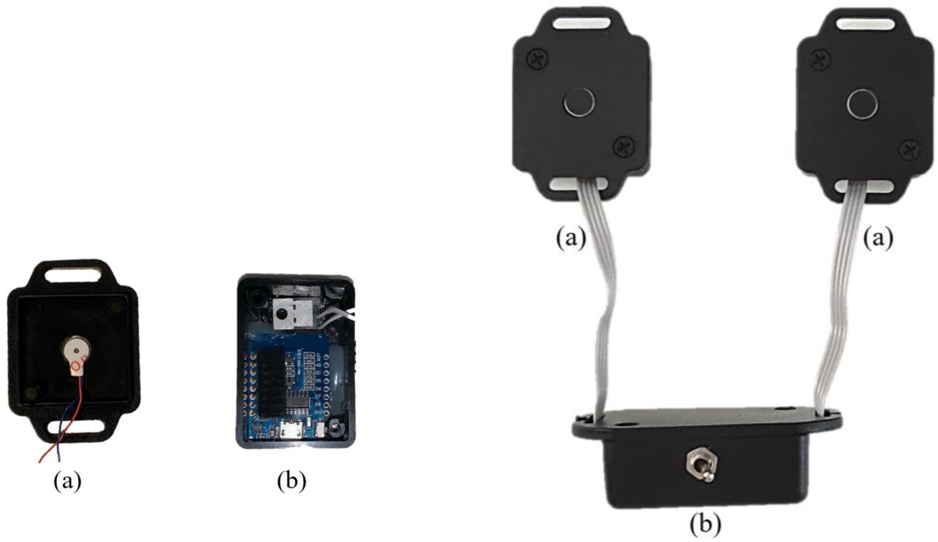


Figure 37. Haptic feedback module. It contains haptic motors (a) and the Wi-Fi microcontroller responsible for the web-socket client (b).

The leg mounted bracelet is attached to the users' skin as per Fig. 35. The vibration units are enclosed within the plastic casing. All the units are sheltered within ABS plastic cases (30x30x10mm) for the haptic module and (40x30x10mm) for the Wi-Fi microcontroller.

Each haptic module contained a vibrating coin motor. It operates on 3V DC and 70mA and it generates a modular vibration of 12000RPM. It is used to give alerts, haptic feedback, and it is light weighed so it can be attached onto user's skin. The design of the circuit contains MOSFET transistors operating as switches. There was also a pulse width modulation control to allow precise change of the intensity of the vibration unit, if required [172, 173]. The frequency of vibration was decided according to literature and guidelines. When the signal is received by the communication unit, the vibrating unit provides a high level TTL output signal to the transistor's gate. This signal leads the transistor to operate in the "saturation region" and permitting the current to reach the motor. A freewheel diode was installed across each motor of the vibration units to remove voltage spikes due to inductive nature of the load when switched off [174]. This prevents malfunction of the hardware, protecting the I/O ports of the microcontroller inside the communication unit from electromotive force (EMF). The circuit is available in Fig. 38.

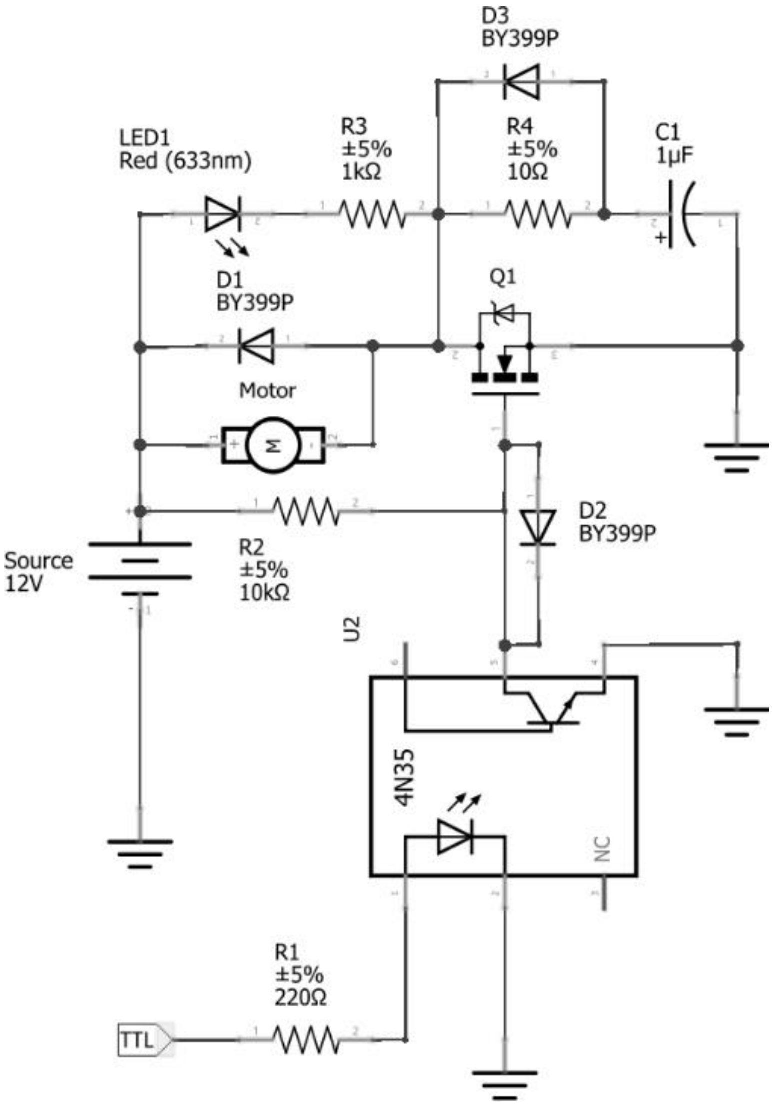


Figure 38. Electronic circuit of haptic module.

4.4.2.2 **Augmented Reality Module**

The AR module consisted of an Epson Moverio Bt-300 Smart Glasses [102] (Fig. 15) connected with a WebSocket protocol [175]. A WebSocket client in the AR module was employed as it allowed the web server to establish a connection with the feedback application and communicate directly with it without any delay (typically web communication consists of a series of requests and responses between the client and the web server, where, for real-time applications, this technique is not well suited [175]). The sequence diagram of the socket architecture is presented in Fig. 39.

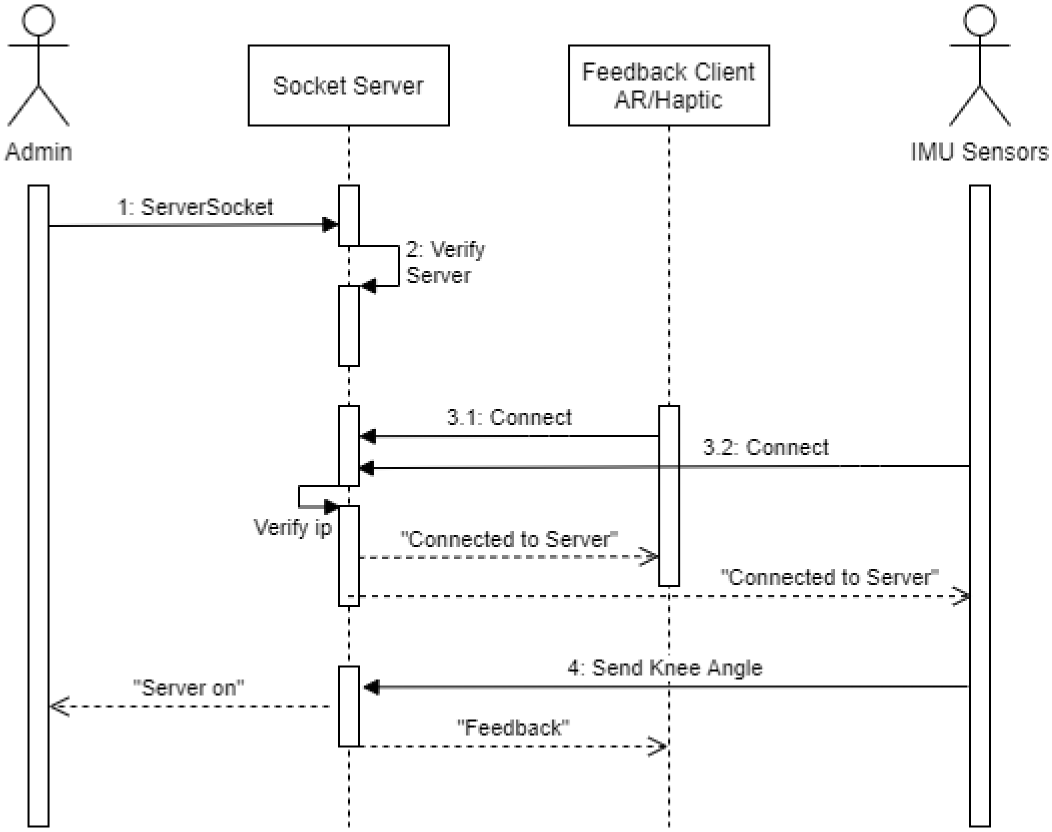


Figure 39. Sequence diagram of the SocketServer

With the use of WebSockets, a connection is established only once, and the communication between the server and the feedback application could follow without problems related to delay and synchronization.

4.4.3 Activation of Feedback Modules

The feedback state diagram is shown in Fig. 40. The user input from the Capturing Module (IMUs) is compared with the kinematic model which controls the feedback mechanism according to the activation threshold. The kinematic model was defined as in Fig. 40, with activation thresholds for each feedback defined at +7° for valgus, and -7° for varus i.e. if valgus/varus angle extended beyond the defined threshold, feedback was provided to the user. These values represent normal angle limits of knee alignment [176].

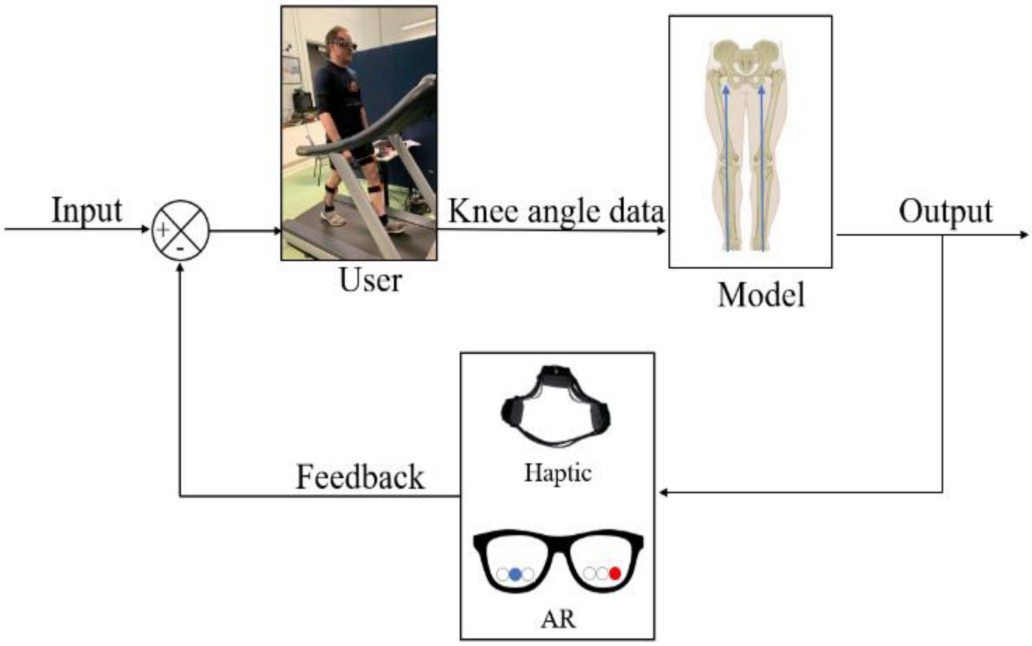


Figure 40. Feedback state diagram. User knee angle is used as input, which will be compared constantly with kinematic model. Adapted from [29].

In this model, every reading from the capturing module is processed and compared with threshold values. Every person has their own walking style and for this reason it is difficult for a participant to have perfect alignment throughout every single part of the gait cycle while walking naturally. The model flowchart is shown in Fig. 41.

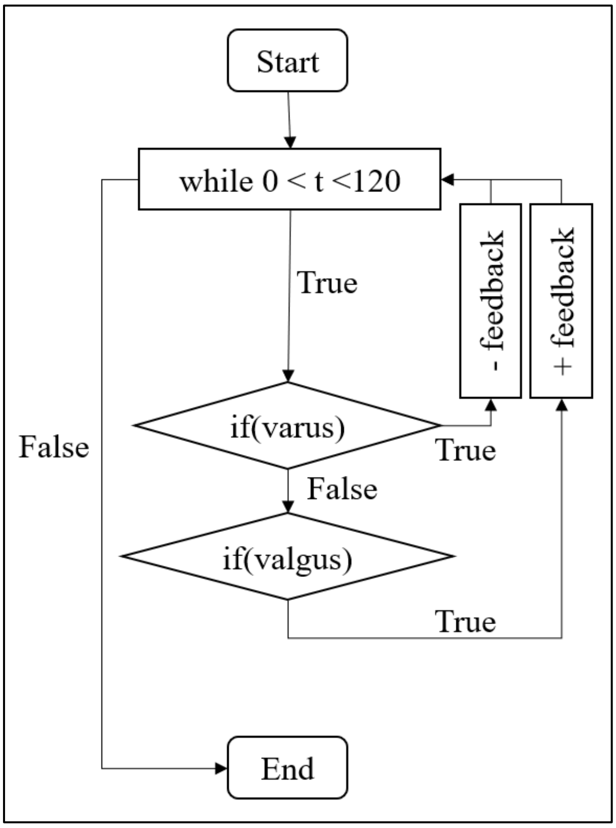


Figure 41. Feedback flowchart. The feedback is given according to the captuting module angle input.

The feedback in the Haptic module was presented as vibrations on each leg whenever the participant's tibial angle was above or below the activation thresholds for valgus and varus. The correct alignment of each leg resulted in "no vibration" (i.e. no feedback provided) on the Haptic bracelet (Fig. 42). The objective given to the participant was to receive the least amount of vibration as possible. This was explained during the training phase which is discussed in detail in section 4.4. Participants were told that no feedback from haptic means they are in correct alignment.

The feedback in the AR module was presented as circle visualizations on the AR glasses. This was presented to the participant whenever the tibial angle was above or below the activation thresholds for valgus and varus. For each leg, three circles control the states of the knee according to valgus and varus angles. The correct alignment of each leg is achieved when the blue circle in the middle is lit. The objective given to the participant is to keep the circles blue during trial. For AR module, user sees a projection of 6 circles in their field of view (3 of each leg as per Fig. 42).

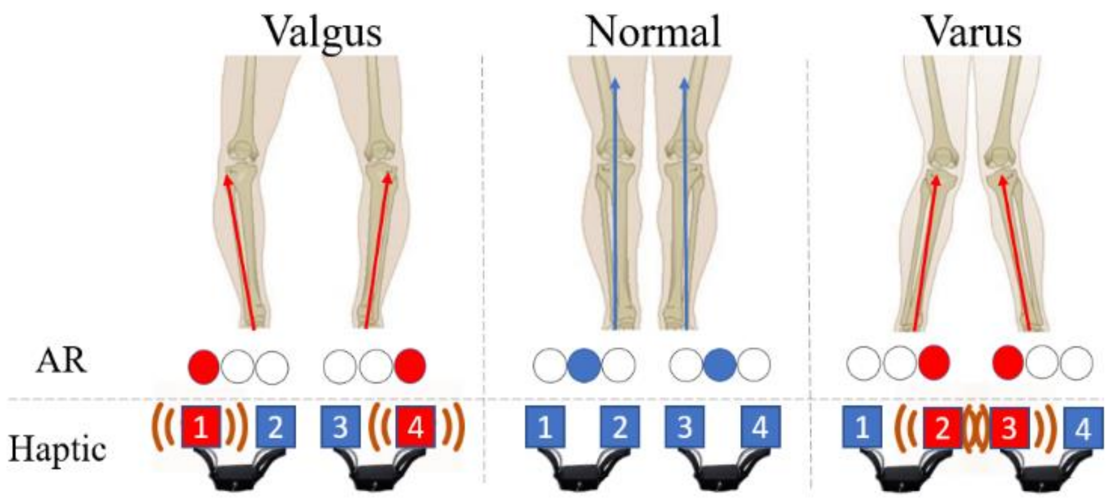


Figure 42. – AR and Haptic feedback activation controls. AR feedback is controlled by coloured circles: red for misalignments and blue for alignment. Haptic controls are vibrations on each leg: 1 and 4 for Valgus, 2 and 3 for Varus. Adapted from [29]

4.5 Experimental Protocol

This study was approved by the Athlone Institute of Technology Research Ethics Committee on the 23rd of January of 2019. Participants consent was obtained in written format and stored in a secure location. Data were anonymized for all trials and participants. After ethical approval, a test with healthy participants was conducted. A convenience sampling approach was employed to recruit twenty-six participants (13 males, 13 females) with an average age of 27.54 (± 6.57) years. Due to previous knee/ walking abnormalities identified via a screening protocol (see section 4.5.1), data from two the participants were omitted. The gender balance guidelines have been applied as per ITU-P913 standards for objective and subjective quality assessment [120]. A within group experimental design was employed; hence each participant experienced both the haptic and AR feedback modalities. The ordering of how the participants experienced the feedback was randomised. Participants were tested on two different days, with at least 7 days between tests [177]. The protocol adhered to the approach taken in numerous related works in the literature [15, 118, 121] and included the steps outlined in Fig. 43.

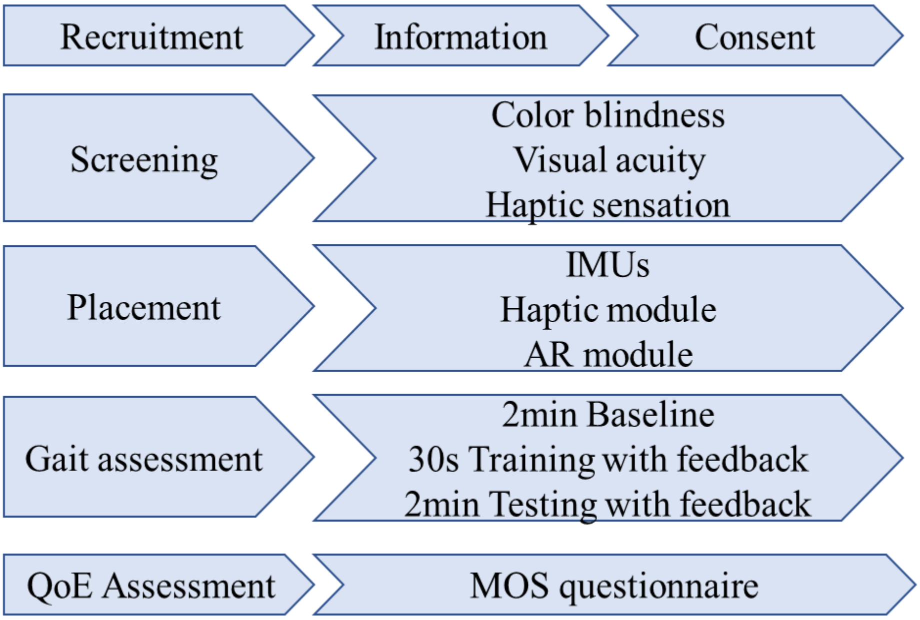


Figure 43. Testing protocol. This protocol was consistent during all trials for all participants.

During the information phase, each participant was greeted and thanked for their participation. After a brief explanation, written consent was obtained. Information and Consent forms are available in Appendix F and G, respectively. Participants were brought to the waiting room and were provided with an information sheet that fully described the experiment. The screening phase assessed participants visual acuity, color perception, and ability to perceive the haptic stimuli, and required achievement of a threshold score to be eligible for testing [178-180]. For the Snellen test, a score of 20/20 was required. For the Ishihara test, thirty-eight color plates were used and only 4 errors were allowed during examination. For the haptic screening, participants were required to differentiate 4 vibration patterns and location [180]. Upon completion, baseline metrics of gait angles in the sagittal plane: left and right hip, left and right knee, and trunk lean were captured over a two-minute period using the sensor system in response to the different feedback modalities outlined in section 4.4.2. It was also captured, left and right tibia (for varus/valgus assessment) in the frontal plane. For this experiment, only tibia angle was analysed to evaluate the effectiveness of the feedback with regard to reducing varus/valgus misalignment. Full gait analysis considering all angles will be evaluated as part of a future work study.

For training and testing phases, participants were randomly assigned into two groups (Haptic/AR, and AR/Haptic) depending on which feedback the participant experienced first. Each participant in a group experienced one of the feedback modalities and had at least a week break before they were presented with the alternative modality feedback. As part of the training, participants were introduced to the AR and the haptic modules as appropriate for the given test day. The devices were fitted to the participant by the principal investigator and an opportunity for adjustment was provided to ensure there was no discomfort. After sensor placement, participants were securely guided to a treadmill where they were asked to select a walking speed with which they felt comfortable. This represented a typical day walking pace (the range selected by users was between 2.5 and 4 miles per hour). Following this, in the test, the speed each participant selected was maintained for training and testing of both feedback modalities. Instructions for each feedback were explained with 3 feedback sheets (available in Appendix H) showing the difference between the three different knee states (valgus, normal, varus). Participants were aware that each leg was independent so that even though one leg was in a valgus state, the other one could be aligned for example. Participants walked 2 minutes for baseline capture (no feedback), 30 seconds for feedback training, and 2 minutes (with feedback). After the test the participant answered questions regarding experience.

4.5.1 QoE MOS Questionnaire

Twelve questions were asked of all participants on the experience of both feedback modalities and answered the questionnaire twice in each testing feedback. For the subjective analysis, QoE factors were evaluated in form of questionnaires after the gait assessment phase as per Fig 43. QoE takes into consideration how system, human and contextual factors contribute to a user's perceived quality of a system [17]. The literature suggests that the accepted approach to measuring a user’s perceived quality of his or her experience is based on self-reported measures via post-experience questionnaires. The developed questionnaire was used to determine an overall mean opinion score (MOS) based on feedback from users [181].

The twelve questions were developed to evaluate system utility (questions 1-3), usability (questions 4-6), interaction (questions 7-9), and immersion (questions 10-12). For each of those 4 assessment variables, 4 standard questionnaires were used as guidelines: The System Usability Scale (SUS), ITU-T methods for subjective assessment of quality, Igroup presence questionnaire (IPQ), and Computer System

Utility Questionnaire (CSUQ) [120, 182-184]. The rating system used was a seven-point Likert scale to determine whether or not the participants agreed with each statement. The full questionnaire is available in Appendix I and per Table 7. The ordering of the questions was randomised for the different participants to negate any ordering effects.

Table 7. MOS Questionnaire

QoE Factor	Question	
Utility	Q1	When I received feedback, I adjusted easily and quickly.
	Q2	My walking style changed during experiment.
	Q3	The system could not be used without the support of an expert.
Usability	Q4	The feedback was easy to understand.
	Q5	I needed to learn a lot of things before I could use the system.
	Q6	The system was difficult to use.
Interaction	Q7	The feedback was clear.
	Q8	I had to concentrate in order to understand what the system expected me to do.
	Q9	The system provided consistent feedback.
Immersion	Q10	I was aware of my body whilst moving.
	Q11	I was aware of the real world surrounding while walking (e.g. sounds, room temperature, other people, etc.)?
	Q12	I was engaged with the system.
Answering Scales		①Strongly Agree / ②Agree / ③More or less Agree / ④Undecided ⑤More or less disagree / ⑥Disagree / ⑦Strong Disagree

4.5.2 NASA-TLX and SAM questionnaires

The Nasa Task Load Index was also part of the subjective analysis of QoE. This tool can determine in six different dimensions, the subjective workload during tests (feedback). The test evaluated mental demand, physical demand, temporal demand, effort, performance, and frustration level [131].

In the context of this work, mental demand was used to evaluate how much thinking was required to process feedback and align legs. Physical demand evaluates the amount of physical activity required to perform alignment. Temporal demand evaluated the amount of time pressure to align legs. Effort assessed how hard the participant had to work to achieve alignment. Performance was related to the level of success in completing the task. Finally, frustration level aimed to evaluate how insecure was the participant during the task. This questionnaire was used to compare AR and haptic feedback workload.

The Self-Assessment Manikin (SAM) scale was used to measure emotion according to the participant's opinion. Participants were asked to mark in a pictorial scale, the affective reaction to the stimuli presented in the test (haptic and AR feedback). This scale aims to measure three dimensions of emotion response: valence, arousal, and dominance. The results of both questionnaires will be presented later in this chapter.

4.6 Data and Signal Processing

As outlined in the methodology section, QoE and objective metrics were captured for each trial. Participants were categorized into AR and haptic. Subgroups of males (N=13) and females (N=13) were also randomly assigned for gender analysis purposes. In order to compare differences across groups, a Shapiro-Wilk normality test [185] was conducted. All variables displayed normal distribution ($p>0.05$). A dependent samples t-test was performed on the data with 95% confidence level to compare both groups. For the objective analysis, differences between AR and haptic groups are examined for number of alignments after receiving feedback, and the amount of time participants were not aligned. The same analysis considering gender is also reported. These comparisons were done by dependent samples t-test at 95% confidence level. The QoE model ($QoEM_F$) for each feedback for a number p of participants was designed to be average of the four-assessment metrics: Utility (UtF), Usability (UsF), Interaction (InF), and Immersion (ImF) as in (eqn. 21).

$$QoEM_F = \sum_{n=1}^{p} \frac{UtF_n + UsF_n + InF_n + ImF_n}{4} \quad (21)$$

4.7 Results

In this section the analysis and discussion of the data captured during the experiment is presented. This includes objective measures of performance (i.e. number of misalignments for each feedback modality); and subjective evaluation from post-test questionnaires (QoE, NASA-TLX and SAM) for each of the feedback modalities. In addition, gender analysis is included.

4.7.1 Objective Results

For the objective data, analysis on how the participant reacted to each of the types of feedback i.e. if or how did they change their walking style based on each feedback modality are presented. For each leg, three distinct states were defined: varus, correct position, and valgus. For each state, the time the participants remained in misalignment during the experiment, and the number of times the participant needed feedback (feedback cue) during the experiment (2 minutes) is reported. The number of complete alignments (both legs in correct position) and misalignments for each leg are also reported.

Table 8 contains performance report of varus and valgus alignment of all participants after experiencing AR feedback. It also includes a further categorization by gender. Table 9 reports the same results for the haptic feedback. The results show statistically significant differences between the AR and Haptic feedback in terms of the number of varus, valgus, and total misalignments for baseline and test. Participants performed better with AR feedback, with a reduction of 31% for varus and 13% for valgus. All reported results considered 95% and 90% confidence interval. Statistically significant differences in performance are reported for the AR feedback in terms of reducing varus and total misalignments with a two-tailed $p < 0.1$ and $p < 0.05$. For gender analysis, the male improved for varus (45% $p = 0.034$) and valgus (18% $p = 0.073$) while females did not have statistically significant improvement. The ordering of feedback did not influence performance ($p > 0.1$).

Table 8. Number of Varus and Valgus and Improvement for AR feedback per gender

Group	Trial	Augmented Reality Feedback		
		Varus	Valgus	Total Misalignments
Participants	Baseline	62.772	59.363	122.136
	Testing	43.272	51.181	94.454
	Sig. (2-tailed)	0.048 **	0.444	0.046 **
	Improvement	33%	13%	22%
		Varus	Valgus	Total Misalignments
Male	Baseline	76.454	74.363	150.820
	Testing	54.818	52	106.818
	Sig. (2-tailed)	0.034 **	0.073*	0.041
	Improvement	45%	18%	33%
		Varus	Valgus	Total Misalignments
Female	Baseline	49.090	44.363	93.454
	Testing	31.727	50.363	82.090
	Sig. (2-tailed)	0.187	0.735	0.632
	Improvement	35%	-13%	13%

* $p < 0.1$, ** $p < 0.05$

Table 9. Number of Varus and Valgus and Improvement for haptic feedback per gender

Group	Trial	Haptic Feedback		
		Varus	Valgus	Total Misalignments
Participants	Baseline	55.2727	61.5455	116.8182
	Testing	47.1364	56.1818	103.3182
	Sig. (2-tailed)	0.359	0.546	0.167
	Improvement	15%	9%	12%
		Varus	Valgus	Total Misalignments
Male	Baseline	71.3636	67.1818	138.5455
	Testing	65.2727	65.0000	130.2727
	Sig. (2-tailed)	0.684	0.841	0.565
	Improvement	9%	3%	6%
		Varus	Valgus	Total Misalignments
Female	Baseline	39.1818	55.9091	95.0909
	Testing	29.0000	47.3636	76.3636
	Sig. (2-tailed)	0.344	0.566	0.187
	Improvement	26%	15%	20%

* $p < 0.1$, ** $p < 0.05$

Table 10 and Table 11 contain performance data in terms of how long users were in the varus and valgus positions during the 2 minutes trials. The data demonstrates that only AR feedback could reduce varus time with statistically significant difference between the baseline and testing. In response to AR feedback participants demonstrated a decrease in the amount of time spent in varus by 11%, valgus by 64% and Total misalignments by 37%. Males, in AR feedback had significant improvement in valgus time (63% $p = 0.047$). The performance for the Haptic feedback increased the number of misalignments with the male group (-49% $p = 0.06$). This suggests that the users were somewhat confused by the haptic feedback similar to what has been previously reported [90]. Statistically significant differences in performance were only reported for the AR feedback in reducing varus and total misalignments with a two-tailed $p<0.05$. The ordering of feedback did not influence performance (p > 0.05).

Table 10. Time in varus and valgus and improvement after AR feedback per gender.

Group	Trial	Augmented Reality Feedback		
		Varus Time (s)	Valgus Time (s)	Total Misalignments Time (s)
Participants	Baseline	76.292	75.566	151.858
	Testing	67.785	26.669	94.454
	Sig. (2-tailed)	0.877	0.039 **	0.040 **
	Improvement	11%	64%	37%
		Varus Time (s)	Valgus Time (s)	Total Misalignments Time (s)
Male	Baseline	66.504	63.934	130.438
	Testing	51.067	23.918	114.985
	Sig. (2-tailed)	0.737	0.047 **	0.439
	Improvement	22%	63%	12%
		Varus Time (s)	Valgus Time (s)	Total Misalignments Time (s)
Female	Baseline	86.080	87.198	173.279
	Testing	84.503	72.299	156.803
	Sig. (2-tailed)	0.915	0.188	0.450
	Improvement	1%	17%	9%

* p < 0.1, ** p < 0.05

Table 11. Time in varus and valgus and improvement after haptic feedback per gender.

Group	Trial	Haptic Feedback		
		Varus Time (s)	Valgus Time (s)	Total Misalignments Time (s)
Participants	Baseline	70.9096	83.6540	154.5637
	Testing	85.6217	75.3399	160.9567
	Sig. (2-tailed)	0.142	0.348	0.635
	Improvement	-21%	10%	-4%
		Varus Time (s)	Valgus Time (s)	Total Misalignments Time (s)
Male	Baseline	58.5155	83.2045	141.7200
	Testing	87.2491	70.4224	157.6617
	Sig. (2-tailed)	0.060 *	0.373	0.460
	Improvement	-49%	15%	-11%
		Varus Time (s)	Valgus Time (s)	Total Misalignments Time (s)
Female	Baseline	83.3037	84.1036	167.4074
	Testing	83.9944	80.2574	164.2517
	Sig. (2-tailed)	0.958	0.736	0.857
	Improvement	-1%	5%	2%

* $p < 0.1$, ** $p < 0.05$

4.7.2 Self-Reported Questionnaire Results

4.7.2.1 **QoE Questionnaire**

Table 12 present results of the MOS self-reported measures via post-test questionnaires. Table IV presents the results considering the gender variable. Since the AR and Haptic groups were randomized repeated measures, a dependent samples t-test was performed on the data with 95% confidence level using the IBM statistical analysis software package SPSS [186]. As per Table 12, out of the 12 questions asked, only Question 1, which asked if whenever the participant received feedback, he or she adjusted easily and quickly, reported a statistically significant difference between AR and Haptic feedback with a two-tailed p value of 0.015, $p<0.05$.

Table 12. MOS Questionnaire Results

QoE Factor	Question	AR		Haptic		
		MOS	***Std. Dev***	***MOS***	***Std. Dev***	***Sig. (2-tailed)***
Utility	Q1	4.458	1.414	3.500	1.588	**0.015 ****
	Q2	4.625	1.469	5.000	1.216	0.367
	Q3	3.083	2.205	2.708	2.331	0.362
Usability	Q4	5.667	0.917	5.458	0.932	0.307
	Q5	4.625	1.377	4.875	1.191	0.366
	Q6	5.000	1.180	4.917	1.613	0.714
Interaction	Q7	5.583	0.881	5.458	0.833	0.479
	Q8	2.542	2.167	2.042	1.944	0.261
	Q9	5.333	1.239	5.208	1.318	0.664
Immersion	Q10	5.250	1.152	5.500	1.022	0.207
	Q11	1.917	2.083	1.708	1.574	0.585
	Q12	5.208	0.932	4.583	1.767	0.100

** $p < 0.05$

The AR group reported a MOS rating of 4.458 whereas the Haptic feedback 3.5 ($p<0.05$). This result is confirmed that even not knowing performance, participants felt the AR feedback was more effective in reducing misalignments. Considering the discussion in section 4.7,1 about how participants responded to the haptic feedback (i.e. increase in misalignments), these results raise an interesting question about the ease of understanding haptic feedback for participants. For all other questions, excluding Question 2, the AR feedback had greater MOS than Haptic feedback (although not statistically significant).

Table 13 presents results of the QoE Questionnaire compared by gender. The female group reported a statistically significant difference between AR and Haptic for Question 1. Male group also reported a statistically significant difference for Question 2 (“My walking style changed during experiment.”) and Question 12 (“I was engaged with the system.”).

Table 13. MOS Questionnaire Results

Male						
QoE Factor	**Question**	**AR**		**Haptic**		
		MOS	***Std. Dev***	***MOS***	***Std. Dev***	***Sig. (2-tailed)***
Utility	Q1	4.417	1.564	3.667	1.723	0.169
	Q2	4.000	1.758	5.250	0.621	0.044 **
	Q3	3.083	2.353	2.667	2.424	0.318
Usability	Q4	5.583	1.164	5.083	1.083	0.111
	Q5	4.667	1.435	4.917	1.083	0.555
	Q6	4.833	1.403	4.583	1.781	0.491
Interaction	Q7	5.417	1.164	5.333	0.887	0.723
	Q8	2.333	2.229	1.583	1.729	0.212
	Q9	5.167	1.337	4.917	1.729	0.555
Immersion	Q10	5.167	1.466	5.250	1.356	0.754
	Q11	1.083	1.505	1.333	1.073	0.536
	Q12	5.083	1.164	3.667	2.059	0.043 **
Female						
QoE Factor	**Question**	**AR**		**Haptic**		
		MOS	***Std. Dev***	***MOS***	***Std. Dev***	***Sig. (2-tailed)***
Utility	Q1	4.500	1.314	3.333	1.497	0.049 **
	Q2	5.250	0.753	4.750	1.602	0.309
	Q3	3.083	2.151	2.750	2.340	0.653
Usability	Q4	5.750	0.621	5.833	0.577	0.754
	Q5	4.583	1.378	4.833	1.337	0.515
	Q6	5.167	0.937	5.250	1.422	0.777
Interaction	Q7	5.750	0.452	5.583	0.792	0.551
	Q8	2.750	2.179	2.500	2.110	0.718
	Q9	5.500	1.167	5.500	0.674	1.000
Immersion	Q10	5.333	0.778	5.750	0.452	0.175
	Q11	2.750	2.301	2.083	1.928	0.314
	Q12	5.333	0.651	5.500	0.674	0.504

** $p < 0.05$

Utility, Usability Interaction, Immersion, and QoEM scores of AR and Haptic feedback compared by gender are shown in Fig. 44. AR feedback showed significant Utility ($p < 0.05$) for the female group, which indicated that females found AR feedback more useful than Haptic feedback for this experiment. This QoE factor is related to adjustment to feedback, changes in walking style and system support.

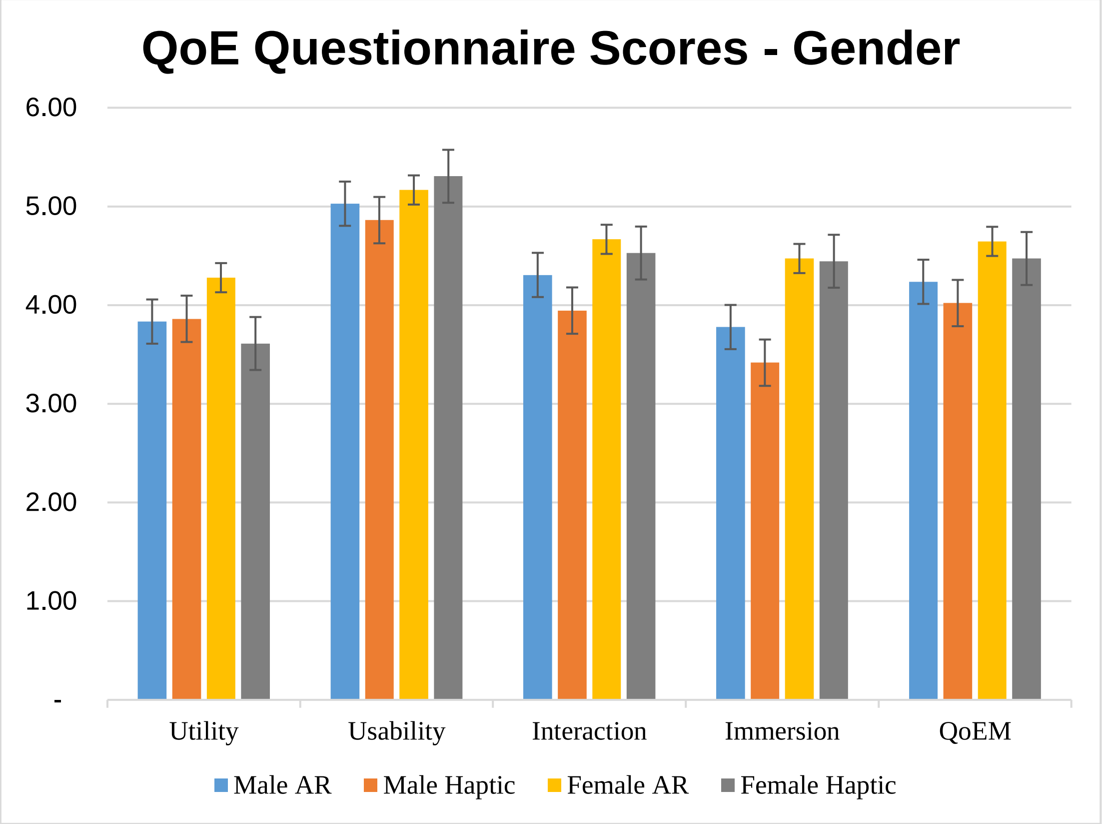


Figure 44. QoE questionnaire scores for AR and Haptic feedback by gender at 95% confidence interval.

4.7.2.2 **Self-Reported NASA-TLX Results**

Weighted Nasa Task Load Index (NASA-TLX) results for haptic and AR groups are presented in Table 14. The group analysis showed a statistically significant difference for physical demand, which showed that haptic feedback demanded higher physical workload when compared to Augmented Reality. There was no statistically significant difference for gender groups.

Table 14. NASA-TLX results – Between groups

Variable	Group	Sig. (2-tailed)	Mean	Std. Deviation	Std. Error Mean
Mental	Haptic	0.836	207.500	127.390	26.003
	AR		215.625	142.488	29.085
Physical	Haptic	**0.019***	151.875	143.329	29.257
	AR		71.458	77.044	15.727
Temporal	Haptic	0.478	66.875	117.147	23.913
	AR		48.333	49.292	10.062
Performance	Haptic	0.230	158.750	113.877	23.245
	AR		120.417	104.173	21.264
Effort	Haptic	0.592	171.042	120.271	24.550
	AR		150.833	138.428	28.257
Frustration	Haptic	0.797	48.333	127.080	25.940
	AR		57.917	129.043	26.341
Mean	Haptic	0.996	44.306	20.813	4.248
	AR		44.278	20.839	4.254

* $p < 0.05$

For all the other variables, there were no statistically significant differences between groups and gender. However, mental demand, physical demand, and performance were variables with high task load index for both groups. These results indicate that the main variables of perceived workload from participants were linked to the mental process for feedback, physical effort required for task completion, and effort in completing feedback task (align legs).

4.7.2.3 Self-Reported SAM Questionnaire Results

Self-reported SAM questionnaire results for haptic and AR groups are shown in Table 15. The results show high valence, arousal, and dominance for AR and haptic feedback. There were no significant differences between gender.

Table 15. SAM results – Between groups

Variable	Group	Sig. (2-tailed)	Mean	Std. Deviation	Std. Error Mean
Valence	Haptic	0.884	7.291	1.944	0.396
	AR		7.583	1.639	0.334
Arousal	Haptic	0.908	6.916	1.442	0.294
	AR		7.041	1.517	0.309
Dominance	Haptic	0.999	6.333	2.180	0.445
	AR		6.333	2.180	0.445

The results of SAM questionnaire showed that participants reported for both groups high affective quality of valence. They also reported high emotional arousal for both groups. Both groups also reported high emotion dominance.

4.8 Discussion

In this section we discuss the results of the comparison between AR and haptic feedback based on the self-reported measures of QoE, NASA and SAM.

Due to the fact that haptic feedback was studied across many fields such as rehabilitation and gait re-education, we had expected that haptic feedback would result in higher objective and subjective scores [84]. Haptic information is given directly at the joint that the user needs to change whilst AR feedback the participant needed to process visual information and change the leg related to that change. Surprisingly, AR feedback could not only reduce the number of misalignments, but the subjective questionnaire analysis demonstrated that users felt that AR feedback was better than haptic for reducing the number of misalignments as asked in Question 1 of the questionnaire (adjustment to feedback).

The results indicate that both feedback modalities reduce the occurrence of varus and valgus misalignments. However, AR feedback significantly reduces the number of varus misalignment (by 31%) when compared to baseline readings. Whilst the reductions for valgus (for AR) and for varus and valgus for haptic were not significant.

Looking deeper at the analysis, surprisingly for the male AR group, the level of reduction for varus was 45% (and 18% for valgus misalignments). Consistent with the male group, although to a lesser extent, AR feedback reduced the number of varus misalignments by 35% for the female group (not significant when compared to baseline). These results demonstrate the utility of employing both feedback types, but in particular AR feedback. It also raises an interesting question as to why females did not display a significant change after receiving feedback. These results are important for the research community and are also a good platform to build on for future work. For example, future research should assess physiological measures and what happens in a clinical setup for males and females. In this way, it will provide a better understanding on the reaction to feedback at physiological level and any correlation (if any).

For the QoE analysis, subjective evaluation questionnaires assessing feedback utility, usability, interaction, and immersion was performed. Table 12 reported results of the MOS questionnaire for all participants. When participants were asked about adjustment after feedback in Question 1 ("When I received feedback, I adjusted easily and quickly."), they felt that AR was more effective in changing varus and valgus misalignments. This agrees with the objective analysis in Table 8. For the MOS questionnaire considering gender, the male group reported that they believed their walking style changed based on the AR feedback. They also reported higher engagement when using the AR glasses than haptic devices. The female group reported higher utility for AR feedback ($p=0.049$). These difference between gender groups highlight the importance of considering human factors and employing QoE analysis in these types of novel feedback studies. The between analysis of the Nasa-TLX showed higher physical demand for haptic group. This variable indicated that the response to haptic feedback is mode physically demanding than AR. SAM questionnaire result showed high valence, arousal, and dominance for both feedback. Although the between analysis of SAM questionnaire was not statistically significant, participants had high emotion control for both modalities, which is a positive result for any of the feedback.

Given that numerous studies have previously investigated various feedback modalities such as 2d visual and haptic, this study provides a new paradigm in using immersive technologies in gait re-training and promotion of rehabilitation and prehabilitation protocols.

4.9 Conclusion and considerations for next study

This chapter presented a comparison of Haptic and Augmented Reality as feedback modalities in a gait analysis system. It compared each modality, in terms of objective and subjective ratings, how users perceived and responded to Haptic and Augmented Reality feedback. Based on the results, the novel AR approach has significant potential as a method of reducing misalignments, and therefore potentially reducing the risk of injury development. The objective evaluation tells us that AR significantly reduces the number misalignments. In addition, the subjective questionnaire assessment provides interesting results in terms of how users perceived positive changes to their gait as a result of AR feedback. The agreement of objective and subjective evaluations serves as basis of using AR as part of a rehabilitation and prehabilitation protocol. Both gender groups considered reported that AR had greater utility than haptic feedback. The male group showed statistically significant improvement in varus, valgus, total misalignment, and valgus time. Future work will also examine if AR feedback not only provides higher QoE scores but also promotes less cognitive workload in comparison with haptic as well as instantiation of the QoE model proposed above.

Next chapter will deal with results of a physiology-based QoE evaluation and bivariate correlations of AR and haptic feedback.

5 Study 2: Physiological-based QoE Assessment of Haptic and AR Feedback in Gait

5.1 Study Aim

After evaluating the gait feedback system for varus and valgus misalignments for haptic and AR feedback, the objective evaluation concluded that AR could reduce the number of varus and valgus misalignments. Also, the subjective evaluation showed higher QoE scores for the AR group when compared to haptic. Subsequently, the aim of this next study is to compare these feedback modalities at a physiological level (e.g. what happens with the skin conductance, heart rate or pupil diameter when a participant interprets and responds to feedback). The analysis also considered gender subgroups.

5.2 Motivation

The rationale for this chapter, and the previous is derived from a need to developing rehabilitation and prehabilitation protocols that not only consider objective improvements in gait, but also assess the user's perspective using the QoE paradigm. This is important as it not only evaluates objectively how a user reacts to feedback but also how they interpret and understand such stimuli, Understanding quality from the user perspective can be a challenging task as it involves many factors such as human, system and context factors as discussed in previous chapters of this dissertation.

The use of subjective evaluation such as the use of questionnaires is a good strategy for quality evaluation [120]. However, subjective assessments are dependent on self-reporting and are "post" the experience. Physiological measures such as heart, skin, and pupil response can be used to understand the human perception and responses after receiving a stimulus and may allow detection and evaluation of cognitive load, emotion, stress, and numerous other factors [187-189].

In quality assessments, physiologic metrics can be used to evaluate the quality of feedback from the user perspective implicitly [190]. This helps to develop a deeper understanding on how users process, understand and react to different feedback modalities. In this context, this chapter reports results of an implicit QoE evaluation of two feedback modalities: Augmented Reality (AR) and Haptic.

5.3 Study Overview

This study is a novel QoE assessment of haptic and AR feedback applied as an overall gait analysis system. For the same experiment described in chapter 5, physiological measures of each participant during baseline and testing were also captured. The data of those 26 participants (13 females and 13 males) included information such as heart IBI (Interbeat interval), heart rate (HR), Electrodermal Activity (EDA) and pupil diameter. The study aimed to assess if these metrics changed based on feedback modality, and gender. It also looked at bivariate correlations that could appear in each of the physiological signals.

5.3.1 Comparison with literature

Physiological signals as user experience metrics are broadly used in many research fields such as biomechanics, signal processing, machine learning, and general medicine [191-193]. These signals contain information that can represent the state of humans such as workload and stress. In this way, the monitoring and interpretation of these signals are significant for researchers, and the rehabilitation itself. This can inform the development of new rehabilitation protocols and help with the success of the rehabilitation.

Rehabilitation studies aim to evaluate and restore lost motor functions in the treatment of motor disabilities or other parameters such as knee alignment or body posture [7, 25]. Traditional rehabilitation approaches have relied on expert guided feedback, which have also used some physiological measures such as electromyography (EMG signals) to evaluate performance [194]. The use of signals such as EMG and Heart Rate Variability (HRV) are applied to assess muscle strength, detect patterns and in the use case of varus and valgus, it is used only to detect activities , muscle strength [195-197], and assess risk of injuries [198].

Nowadays, potential opportunities exist to employ the use of different physiological metrics such as EDA from skin conductance, and pupillometry (pupil dilation/contraction) during feedback to provide a more detailed understanding of the user`s perceptual and emotional state, hence it can improve the quality of rehabilitation.

There are some authors that have previously used physiological signals in evaluating QoE. [134] developed a QoE assessment of VR and AR, which integrated measures of skin through EDA, and HR. The authors concluded that AR was better than VR with less incorrect responses, and in terms of physiological measures, there was a consistency for metrics of EDA and HR for both groups. Other examples include several surveys and literature reviews on the use of physiological and psychophysiology-based QoE [190, 199].

5.3.1.1 **Heart Rate Variability (HRV)**

HRV is a metric that includes heart variation over Inter-Beat Intervals (IBI) and Heart Rate (HR). The literature states that variables of HRV can detect heart abnormalities, and these variables can also be related to emotion arousal, for example [200, 201].

HRV has shown to be reduced in individuals with acute time pressure, which is a psychological stress that occurs when a person has less time available. HRV has shown to be reduced with patients with elevated anxiety state when in focused attention [202, 203]. During walking, HRV is shown to increase when participants have longer walking distance [203].

The Inter-Beat Interval (IBI) is the time interval between two successive R waves (including an R wave) [204]. In the sinus rhythm, the R-R interval must be constant. Its duration depends on the heart rate. This measure can be used to estimate heart rate. In the E4 sensor, IBI is derived from the Blood Volume Pulse (BVP).

HR is a metric that responds to stress [189]. Biologically, mental stress can therefore lead to increased platelet activation, increased blood viscosity and acute reductions in plasma circulating volume. Cardiovascular responses mainly result in an increase in HR and blood pressure. For this study, mean values of IBI and HR were calculated at baseline, prior to testing each event of varus, valgus, and misalignments. These variables are relevant for QoE studies as they can not only report group physiological responses, but it can also indicate specific events that are linked to stress and attention.

5.3.1.2 Electrodermal Activity (EDA)

EDA is a metric that is linked to Skin Conductance Response (SCR). It is also known as galvanic skin response (GSR), electrodermal response (EDR), psychogalvanic reflex (PGR), sympathetic skin response (SSR) and level of conductivity of the skin (SCL) X. It is possible to visualize EDA responses before and after an event such as feedback as per Fig. 45.

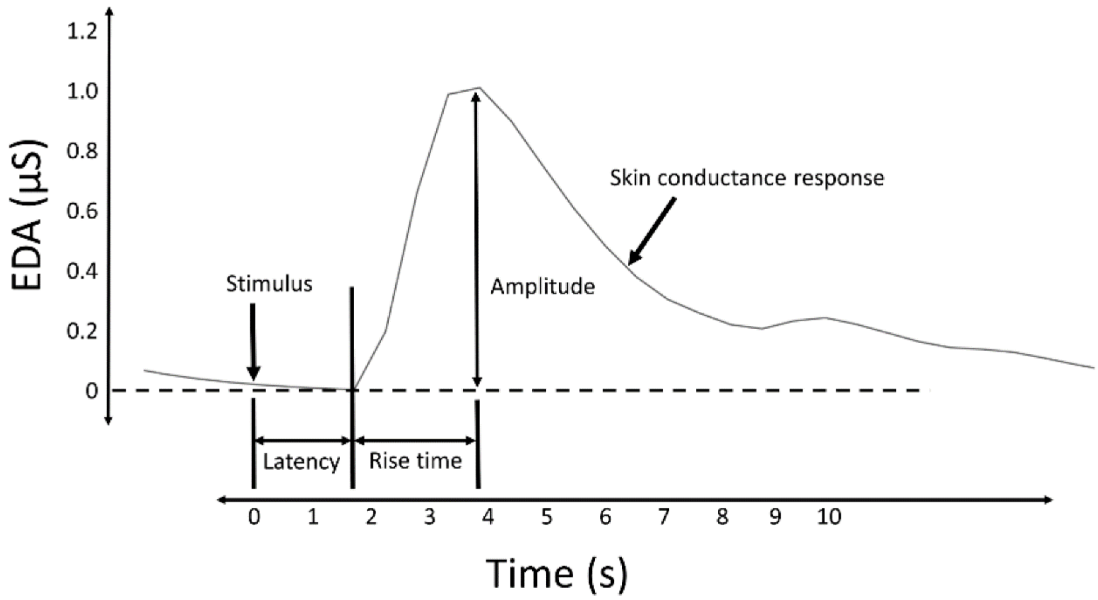


Figure 45. EDA responses after a stimulus. Extracted from [205]

The traditional EDA approaches states that skin resistance varies according to the state of sweat glands in the skin X. Sweating is controlled by the sympathetic nervous system, and the conductance of the skin is an indication of psychological or physiological arousal [188]. If the sympathetic branch of the autonomic nervous system is highly excited, then sweating the gland's activity also increases, which in turn increases the conductance of the skin. In this way, skin conductance can be a measure of emotional and sympathetic responses, which is important for QoE studies [206].

EDA is a common measure of autonomic nervous system activity, with a long history of being used in psychological research. Many biofeedback therapy devices use EDA as an indicator of the user's stress response in order to help the user control anxiety. EDA signal is often combined with recording heart rate, respiratory rate, and blood pressure, because they are all autonomously dependent variables [207].

Beyond traditional event-related SCRs analysis by comparing the amplitude of individual peaks against a pre-stimulus baseline, there are other methods of analysing EDA signals [205]. Some of these methods include the analysis of signal derivatives and frequency domain analysis. To highlight changes in the skin conductance first and second derivatives can be used to detect peaks and sudden changes and peak shifts in the skin conductivity [188]. EDA signals are also known to be detected at some specific frequencies. The separation of the signal according to these values help to detect true EDA events and remove signal artifacts. For frequency values, SCR events are detected at bandwidths of 0.05 to 0.1 (F0SC), 0.1 to 0.2 (F1SC), 0.2 to 0.3 (F2SC) and 0.3 to 0.4 (F3SC) Hz as per some studies in literature [187, 188].

To the best of the authors knowledge, the use of metrics such as EDA, HR, pupil, is a topic that is not yet deeply explored in gait and gait feedback, however is important as it provides important information about how the user implicitly responds and processes feedback and as such is one of the key novel parts of this work.

5.3.1.3 **Pupillometry**

The study of the pupil has become a very useful element for studying the autonomic nervous system. It is based on the measurement of pupil diameter under certain conditions and stimuli. The evaluation is part of the neuroophthalmological examination, mainly in the evaluation of the afferent and efferent optical pathway [208]. The pupil is directly connected to the iris with the function of controlling the amount of light that enters the eyes. The dilation of the pupil has also been shown to be related to the brains response of stressful situations, and therefore provides useful information in a QoE assessments [209]. On occasions that take away comfort, the sympathetic nervous system stimulates the production of a high adrenaline load, a hormone that, in turn, induces pupil dilation as in Fig. 46. On the other hand, the tendency is for it to remain contracted in situations of rest or less stress.

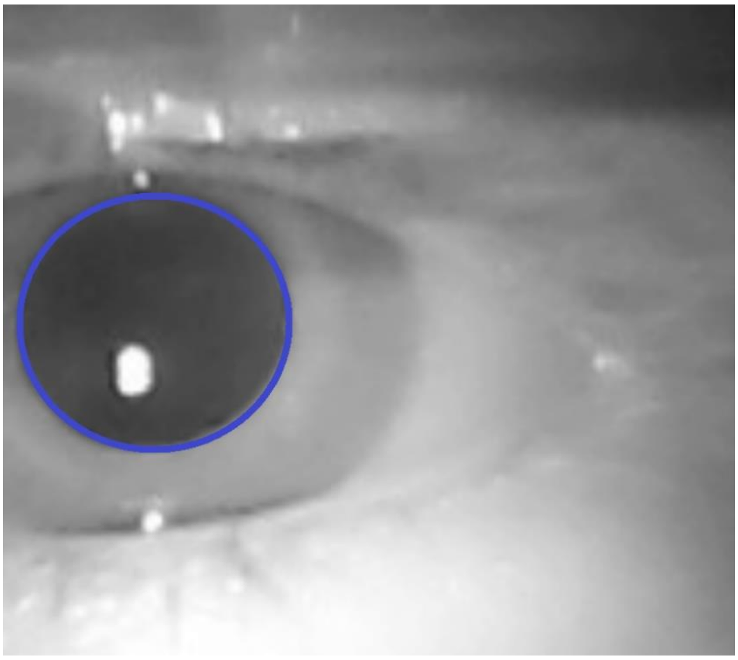


Figure 46. Pupil dilation after stimulus.

The pupil size varies between 1mm (miosis) and 8mm (mydriasis) [210]. Under normal conditions, they are symmetrical in shape, position and are approximately the same size, with a difference of up to 0.4 mm being considered normal, although some authors consider differences of up to 1 mm are still considered normal [211]. Pupils tend to dilate in situations of sympathetic activation (fear, joy, surprise)[212]. However, the evaluation of the pupil is very subjective, as its responses translate into small changes in their diameter. In addition to having several clinical applications, the study of the pupil is still widely used in psychology and in QoE studies to verify the reaction after a stimulus [190, 213], which gives more information of the physiological state of participants.

The remainder of this chapter explores the use of physiological and subjective measures in the gait feedback study. The study design, experimental protocol, results and also a discussion is presented.

5.4 System Design

The system design for this study considered the capture of physiological measures. These metrics were captured offline and data were processed by a system in a quadcore Intel Core i7 laptop, 16GB DDR4 RAM, 3.2Ghz, GTX 1060-6GB. Data capture was achieved with the Empatica E4 wristband ([214] and Fig. 47) for EDA, and IBI (inter-beat interval for HR).

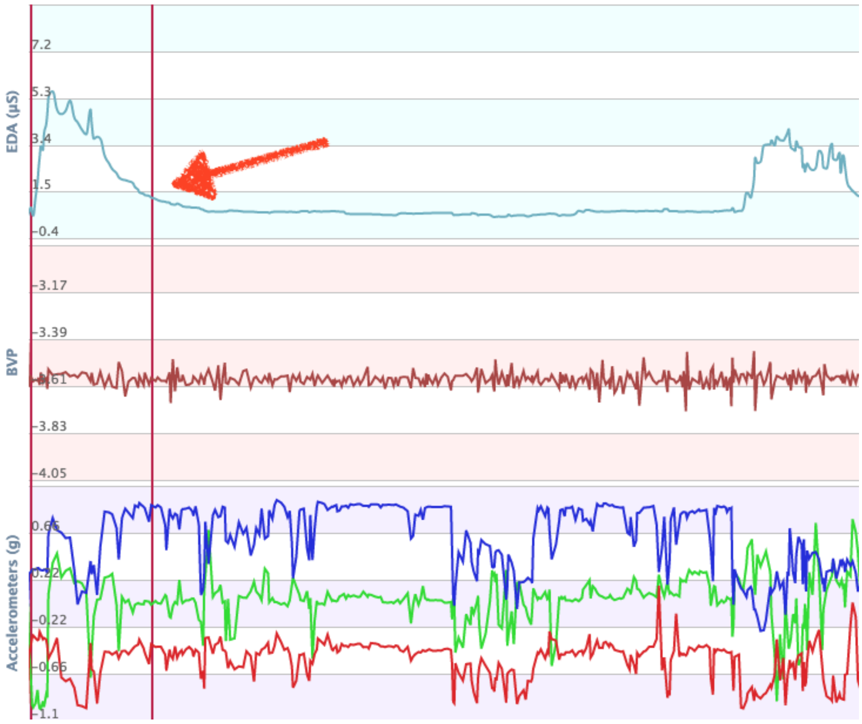


Figure 47. E4 data visualization. Available at [214].

The E4 is a medical certificated sensor that consists of a Photoplethysmography (PPG) sensor, which can measure Blood Volume Pulse (BVP), Heart Rate (HR), Heart Rate Variability (HRV), and other cardiovascular features that can be derived. It also contains a 3-axis accelerometer, and an Electrodermal Activity (EDA) sensor, which can measure sympathetic nervous system arousal [215].

Pupil information was captured with the Binocular Mount Add-on for the Epson Moverio BT-300 from Pupil Labs [216] (Fig. 48). This add-on can provide low-latency eye tracking pipeline to detect saccades and quick fixations [213, 217].

Figure 48. Eye tracking add-on for Moverio BT-300. Available at [216].

5.5 Experimental Protocol

The data for this experiment was captured as part of the e study described in the previous chapter. Participants consent was obtained in written format and stored in a secure location. Data were anonymized for all trials and participants. After ethics approval, a test with healthy participants was conducted. This test also considered the capture of physiological measures from E4 and pupil information from the eye tracking.

The gender balance guidelines have been applied as per ITU-P913 standards for objective and subjective quality assessment [120].

5.6 Data and Signal Processing

As outlined in the experimental protocol section, subjective metrics from questionnaires and physiological measures of EDA, IBI, and pupil were captured. Participants data were categorized into AR and haptic. Subgroups of males (N=13) and females (N=13) were also randomly defined for gender analysis purposes. In order to assess the suitability of the data for parametric analysis, a Shapiro Wilks normality test was conducted [185]. All variables were with a normal distribution ($p>0.05$).

The data from E4 was captured with the E4 connect from Empatica, which separates each trial into different .csv files of acceleration, blood volume pressure, electrodermal activity, heart rate and inter beat interval. Those files were also synchronized with different leg events using UNIX timestamps.

5.6.1 Event based analysis

For all trials, data from E4 and pupil sensors were sliced and synchronized with the timestamps from the objective data from the experiments detailed in the previous chapter. Trials were categorized as baseline (2 minutes data without feedback), test (2 minutes data with feedback), varus (2 legs misaligned with feedback), valgus (2 legs misaligned with feedback), 2 error (2 legs misaligned varus or valgus with feedback), 1 error (one leg misaligned with feedback), and complete alignment (both legs aligned with feedback). Each leg had 3 different states as in 1,2,3 for left leg, and 4,5,6 for the right leg. This way, the 9 possible states are defined as in Table 16.

Table 16. Event-based states

State (L - R)	Left Leg	Right Leg	Output
1 - 4	Varus	Valgus	2 errors
1 - 5	Varus	Alignment	1 error (Varus)
1 - 6	Varus	Varus	Varus
2 - 4	Alignment	Valgus	1 error (Valgus)
2 - 5	Alignment	Alignment	Complete Alignment
2 - 6	Alignment	Varus	1 error (Varus)
3 - 4	Valgus	Valgus	Valgus
3 - 5	Valgus	Alignment	1 error (Valgus)
3 - 6	Valgus	Varus	2 errors

For all groups a between and within analysis was performed. The motivation for this analysis was to identify significant differences across groups and within groups. The between and within gender analysis was also included. Normalities test and a pre-test on baselines were conducted to ensure the samples followed normal distributions and that there were no statistically significant differences across baselines (AR and haptic baseline).

For the between analysis, the analysis of covariances (ANCOVA) was performed. Effect interactions were also reported to make sure the difference is explained by covariances. Gender was a factor to check any interaction effect. Firstly, it was checked if there was any statistically significant difference between baselines. Secondly, homogeneity test for variables were made to ensure normal distributions and then checked any interaction effects.

After the between analysis, a within analysis considered dependent samples t-test with 95% confidence level. In this analysis, differences (before and after feedback) were analysed for AR and haptic groups. The within analysis considering gender is also reported. In this analysis, it was considered event-based comparisons to check what happens before and after an event (e.g. How does the heart rate change when a participant aligns both legs?)

5.6.2 Heart Rate Variability Analysis

The Heart Rate Variability (HRV) analysis included the signals of Inter-Beat Interval (IBI) and Heart Rate (HR) (captured with the E4 sensor). These are important variables as they can be related to emotional arousal and anxiety for example as mentioned in the previous section.

The extracted IBI file contained a UNIX timestamp, with heterogeneous frequency, which made it hard for time-based analysis. IBI analysis is done for many studies for static conditions, studies with low motion, and in case of high motion studies, it is advisable to use the calculated HR [218, 219]. In this analysis, mean values of HRV metrics were used and synchronized with alignment events.

5.6.3 EDA Analysis

The EDA analysis included time-domain analysis of SCR, and frequency domain analysis of the EDA signal. The time domain analysis was done in an event-based manner. For each EDA signal, mean and standard deviation of derivatives for each event were calculated. The variables of the time domain of EDA are presented on Table 17. These variables are important as they not only represent EDA during feedback (compared to baseline) but also how is EDA changing after different user responses to feedback such as alignment, and misalignments. Additionally, frequency analysis and derivatives can give a better understanding of true EDA events and filter signal artifacts.

Table 17. Time Domain Analysis – Electrodermal Activity analysis (EDA).

Indicator	**Description**
mEDA	Mean of all EDA (Test and baseline).
m1Der	Mean of first derivative of EDA signals. Detects EDA events.
m2Der	Mean of second derivative of EDA signals. Detects EDA events and signal concavity.
mEDAVarus	Mean of all EDA (Test and baseline varus).
m1DerVarus	Mean of first derivative of EDA signals. Detects EDA events for varus.
m2DerVarus	Mean of second derivative of EDA signals. Detects EDA events and signal concavity for varus.
mEDAValgus	Mean of all EDA (Test and baseline valgus).
m1DerValgus	Mean of first derivative of EDA signals. Detects EDA events for valgus.
m2DerValgus	Mean of second derivative of EDA signals. Detects EDA events and signal concavity for valgus.
mEDAAlign	Mean of all EDA (Test and baseline complete alignment).
m1DerAlign	Mean of first derivative of EDA signals. Detects EDA events for complete alignment.
m2DerAlign	Mean of second derivative of EDA signals. Detects EDA events and signal concavity for complete alignment.
mEDA2E	Mean of all EDA 2 legs misaligned (varus, valgus, one leg varus other valgus, etc).
m1Der2E	Mean of first derivative of EDA signals. Detects EDA events for 2 legs misaligned (varus, valgus, one leg varus other valgus, etc).
m2Der2E	Mean of second derivative of EDA signals. Detects EDA events and signal concavity for 2 legs misaligned (varus, valgus, one leg varus other valgus, etc).
mEDA1E	Mean of all EDA 1 leg aligned.
m1Der1E	Mean of first derivative of EDA signals. Detects EDA events for 1 leg aligned.
m2Der1E	Mean of second derivative of EDA signals. Detects EDA events and signal concavity for 1 leg aligned.

5.6.4 Pupil Analysis

The pupil analysis in this study included the analysis of baseline, test, and all single events linked to leg alignments. It also considered how the pupil dilation changed prior to and after each event, which is used to assess if there is any change regarding the pupil dilation. The variables of pupil are specified in Table 18.

Table 18. Pupil variables for analysis

Indicator	Description
Mean results (z-scores)	
Baseline	Pupil baseline capture
Test	Pupil test capture
2R	Both legs aligned
1A	One leg aligned
2E	Both legs misaligned.
Event-based results (z-scores)	
2E1R	Participant had 2 mistakes and corrected one leg.
1R2E	Participant had 1 leg aligned and now has 2 mistakes.
2R1E	Participant had 2 legs aligned and now has 1 mistake.
1E2R	Participant had 1 leg aligned and now has 2 aligned.

5.7 Results and Discussion

This section deals with the results of the physiological and subjective measures. For all measures, results are reported between groups and gender, within groups and gender. The full statistics report is presented in Appendix J.

5.7.1 Heart Rate Variability Results

5.7.1.1 **IBI**

Results from IBI between groups are presented in Table 17.

Table 19. IBI results between groups

Variable	Normal	Sig(2-tailed)	F	ETA Sq.	Haptic	Std.	AR	Std.
MNN	0.517	0.792	0,071	0.004	0.748	0.161	0.754	0.22
SDNN	0.489	0.341	0.958	0.053	0.061	0.023	0.094	0.07
RMSSD	0.146	0.185	1.912	0.101	0.088	0.032	0.117	0.04

The results showed no interaction effect was found for variables of IBI between groups. These results are reporting that both groups showed similar mean for IBI values There was no interaction for gender for AR and haptic groups. It is important to know that IBI measures can be less accurate during walking. The literature suggests that the use of HR in this case is recommended to remove artifacts that can be captured during movement [220]. More information will be reported in the HR analysis. Within group analysis of IBI is shown in Table 20.

Table 20. IBI results within groups

Haptic					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
MNN_Baseline	0.436	0.709	0.110	0.599	0.820
MNN_Test		0.749	0.161	0.587	0.910
SDNN_Baseline	0.297	0.095	0.071	0.024	0.166
SDNN_Test		0.062	0.023	0.039	0.085
RMSSD_Baseline	0.358	0.106	0.043	0.062	0.149
RMSSD_Test		0.088	0.032	0.056	0.120
AR					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
MNN_Baseline	0.166	0.699	0.170	0.528	0.869
MNN_Test		0.754	0.227	0.527	0.982
SDNN_Baseline	0.226	0.065	0.031	0.034	0.096
SDNN_Test		0.095	0.071	0.024	0.166
RMSSD_Baseline	0.205	0.089	0.043	0.046	0.133
RMSSD_Test		0.118	0.045	0.073	0.163

As per Table 20, there was no interaction effect within groups. The gender analysis showed no significant difference by gender and groups. It was not possible to analyse IBI for all events as this is a metric difficult to be captured when in motion (i.e. walking, sprinting). However, event-based heart metrics were estimated with HR, which are fine in this kind of analysis.

5.7.1.2 **Heart Rate**

For HR, there was no statistically significant difference between baselines ($p = 0.431$) and the samples followed normal distributions ($p = 0.342$). The between analysis included parallel differences between groups for each event (varus, valgus, 2 misalignments, 1 alignment, and complete alignment). Results from HR between groups are presented in Table 21. A statistically significant difference for range of HR for full alignment was observed for AR when compared to haptic. The AR group showed a lower range of HR, which could infer that participants cardiac response was elevated with haptic feedback.

Table 21. Parallel differences in each event – Between groups

Group (1 haptic 2 AR)		Sig. (2-tailed)	Mean	Std. Deviation
meanHR	1	0.753	-1.885	18.213
	2		-0.303	15.606
rangeHR	1	0.054	-2.600	11.464
	2		6.101	17.640
meanHRvarus	1	0.298	-3.857	8.763
	2		0.883	3.745
rangeHRvarus	1	0.528	-7.538	15.453
	2		-0.987	6.462
meanHRvalgus	1	0.898	-4.994	18.600
	2		-5.800	6.875
rangeHRvalgus	1	0.187	-7.540	12.471
	2		1.115	14.183
meanHRalignment	1	0.316	-3.511	20.196
	2		2.424	17.076
rangeHRalignment	1	**0.033***	-5.272	11.573
	2		4.874	17.955
meanHR2E	1	0.848	-2.195	18.543
	2		-1.180	13.043
rangeHR2E	1	0.095	-4.640	11.728
	2		2.939	15.473
meanHR1A	1	0.708	-2.316	18.698
	2		-0.459	14.470
rangeHR1A	1	0.089	-5.399	11.880
	2		2.137	17.027

* $p < 0.05$

Further analysis by gender did not show statistically significant differences for any variable. Full report is shown in Appendix J.

5.7.2 EDA Results

This section reports results of electrodermal activity (EDA) considering time domain and frequency domain results.

5.7.2.1 **Time Domain Results**

Results from EDA between groups are presented in Table 22. First, it was checked if there was any statistically significant difference between baselines. Secondly, sphericity test for variables were made for the variables mEDA (mean of signals EDA), 1derEDA (first derivative EDA), and 2derEDA (Second Derivative EDA). There were no statistically significant differences between variables between groups and gender.

Table 22. EDA results between groups

Variable	Normal	Sig(2-tailed)	F	ETA Sq.	Haptic	Std.	AR	Std.
mEDA	0.517	0.792	0,071	0.004	0.748	0.161	0.754	0.22
1derEDA	0.489	0.341	0.958	0.053	0.061	0.023	0.094	0.07
2derEDA	0.146	0.185	1.912	0.101	0.088	0.032	0.117	0.04

Results from EDA within groups are presented in Table 23. Statistically significant differences were found in haptic feedback for mean of EDA, mean EDAC3C4 (valgus), mean C2C5 (complete alignment), and mean 1A (1 leg aligned). AR feedback showed statistical differences for mean EDAC3C4 (valgus), mean C2C5 (complete alignment), and mean 1A (1 leg aligned). All these variables demonstrated that mean EDA increased after receiving haptic and AR feedback.

For gender analysis, male group reported significant differences for haptic feedback for mean EDA, mean EDAC2C5 (complete alignment), and mean 1A (1 leg aligned). For haptic feedback, the male group reported a significant difference for valgus. All these variables reported higher mean of EDA when receiving feedback. Surprisingly, the female group did not show any statistically significant difference for any feedback type (Appendix J).

Table 23. EDA results within groups

Haptic					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
mEDABaseline	**0.025***	0.373	0.671	-0.298	1.045
mEDATest		0.528	0.862	-0.333	1.390
mEDABaseline	0.097	0.281	0.179	0.102	0.461
mEDAC1C6		0.350	0.219	0.131	0.568
mEDABaseline	**0.048***	0.533	0.957	-0.425	1.490
mEDAC3C4		0.682	1.128	-0.447	1.810
mEDABaseline	**0.047***	0.411	0.733	-0.322	1.145
mEDAC2C5		0.567	0.937	-0.369	1.504
mEDABaseline	0.065	0.433	0.766	-0.332	1.199
mEDA2E		0.610	0.941	-0.332	1.551
mEDABaseline	**0.022***	0.373	0.671	-0.298	1.045
mEDA1A		0.522	0.843	-0.321	1.365
AR					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
mEDABaseline	0.068	0.287	0.485	-0.198	0.772
mEDATest		0.458	0.773	-0.314	1.231
mEDABaseline	0.280	0.593	1.027	-0.435	1.620
mEDAC1C6		0.837	1.465	-0.628	2.302
mEDABaseline	**0.004***	0.231	0.148	0.083	0.380
mEDAC3C4		0.283	0.168	0.115	0.451
mEDABaseline	**0.020***	0.287	0.485	-0.198	0.772
mEDAC2C5		0.404	0.657	-0.253	1.061
mEDABaseline	0.128	0.317	0.528	-0.212	0.845
mEDA2E		0.549	0.956	-0.407	1.505
mEDABaseline	0.090	0.287	0.485	-0.198	0.772
mEDA1A		0.461	0.788	-0.328	1.249

* $p < 0.05$

5.7.2.2 Frequency Domain Results

It is important to assessed data in the frequency domain in order to detect true EDA events and remove signal artifacts [221]. Following the literature, true EDA signals are found between 0-0.4hz. The different spectral bandwidths of EDA signals are found in Table 24 and Figure 49.

Table 24. EDA results within groups

Indicator	Description
F0SC	The spectral power in bandwidths 0.05 to 0.1
F1SC	The spectral power in bandwidths 0.1 to 0.2
F2SC	The spectral power in bandwidths 0.2 to 0.3
F3SC	The spectral power in bandwidths 0.3 to 0.4

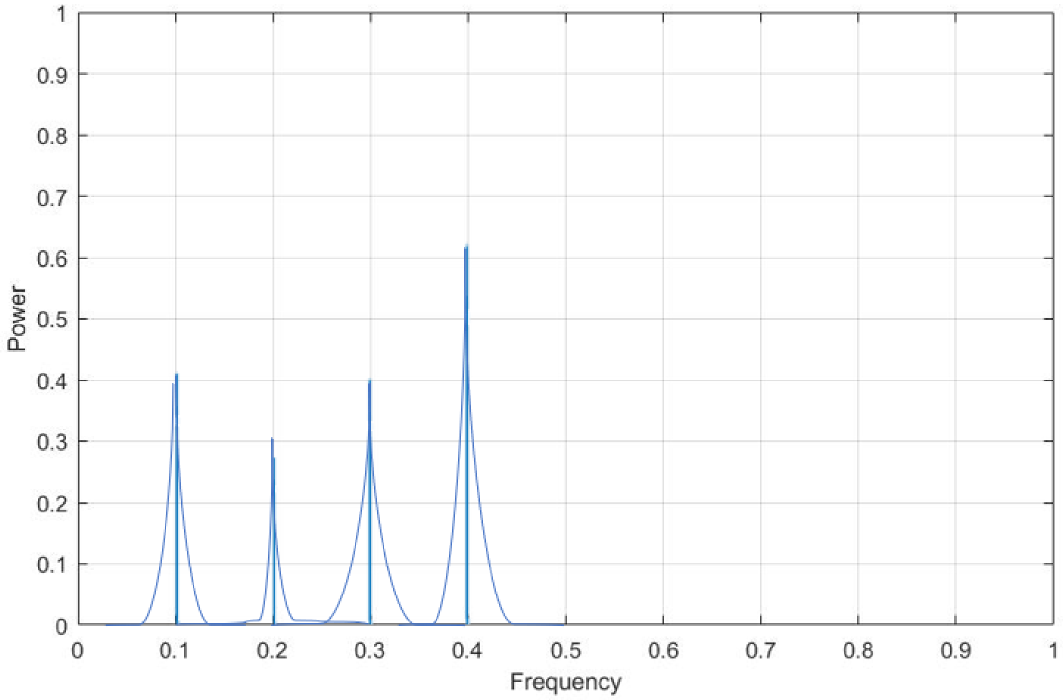


Figure 49. Example of frequency spectrum of EDA signal

Spectral results showed frequency-based EDA for both haptic and AR feedback. It was also compared paired differences within haptic and AR groups. Significant differences for spectral F0SC within haptic feedback were found in EDA baseline-test (Sig. 0.033), and baseline-EDA 1A (1 leg aligned) (Sig. 0.04). Higher spectral power found for baseline EDA 1A, which can infer that more true EDA signals were reported when the participants had only one leg aligned. The AR group did not report statistically significant F0SC frequencies.

Statistically significant differences of F1SC were found in haptic feedback in EDA baseline-test (Sig. 0.038). F1SC frequencies were also found for AR feedback in EDA baseline-EDA 1A (1 leg aligned) (Sig. 0.04).

Statistically significant differences of F2SC were found in haptic feedback in EDA baseline-test (Sig. 0.041). F2SC frequencies were also found for AR feedback in EDA baseline-EDA 1A (1 leg aligned) (Sig. 0.05). The results did not show any F3SC frequencies for any variable of EDA.

Although these results are not in time-domain, they are important because they show where true EDA signals could be found for the presented dataset and help to understand human reaction of feedback considering skin conductance. More results considering EDA signals will be discussed in the section 5.7.4 regarding bivariate correlations.

5.7.3 Pupil Analysis Results

First, it was checked if there was any statistically significant difference between baselines. Secondly, sphericity test for variables were made for the variables of pupil. There were three events for pupil: 2 Error (both legs misaligned), 1 Error (1 Leg misaligned), 2 Right (both legs aligned). There was a significant pupil dilation (increase in diameter) for AR feedback for 2 right and 1 Error but not significant. There was a significant pupil dilation for haptic feedback when both legs were misaligned, which can show a stressful state (Table 25). These differences are also shown in Fig. 50. No difference was found between gender.

Table 25. Pupil results between groups

Variable	Normal	Sig(2-tailed)	F	Haptic	Std.	AR	Std.
m2Right	0.409	0.961	0.002	-0.002	0.288	0.003	0.370
m1Right	0.861	0.736	0.115	0.031	0.207	0.052	0.198
m2Error	0.345	**0.037***	4.681	0.188	0.501	-0.106	0.329

* $p < 0.05$

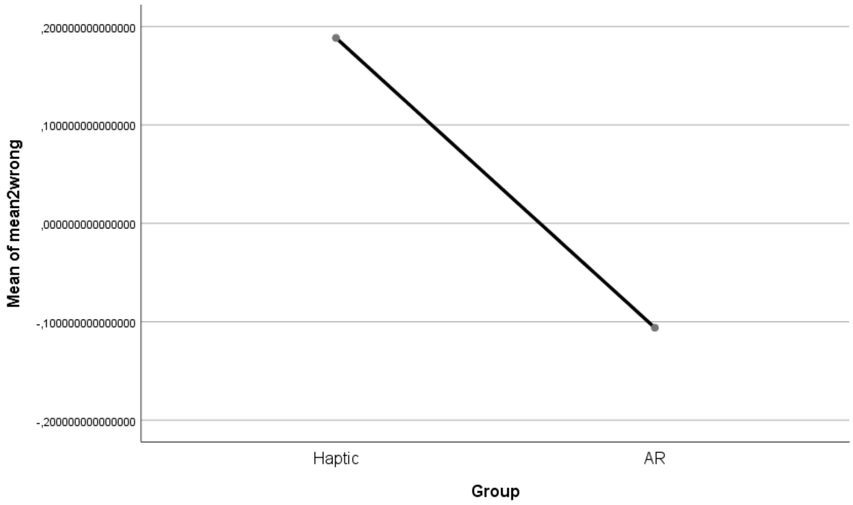


Figure 50. Z-score pupil diameter for 2 misaligns.

For pupil diameter, both means of each state and event-based differences were assessed. For example, if a participant aligns two legs, pupil diameter was evaluated before and after that total alignment. The event-based results of pupil are shown in Table 26.

Table 26. Event-based results of pupil – Between groups

Group (1 haptic 2 AR)		Sig. (2-tailed)	Mean	Std. Deviation
mean2E1R	1	**0.049***	-0.095	0.308
	2		0.152	0.360
mean1R2E	1	0.091	0.144	0.381
	2		-0.099	0.410
mean2R1E	1	0.288	0.064	0.446
	2		-0.089	0.451
mean1E2R	1	0.179	-0.123	0.380
	2		0.023	0.293

* $p < 0.05$

The results of Table 26 showed that pupil diameter increased when participant aligned one leg for AR feedback. The results also showed that there was a relaxation of pupil for haptic feedback for the same event type.

There were no significant differences between baselines and testing, however significant differences were observed between AR and Haptic. Within analysis of the female group for haptic feedback demonstrated that pupil diameter increased when females achieved full alignment (p = 0.016), which may indicate that finding alignment in response to haptic feedback may cause stress for the female group. No statistically significant differences were found for the male group.

5.7.4 Bivariate Correlations

Another way to check the influence of physiological variables and its effects on subjects is through bivariate correlations. It is well known that correlation does not necessarily mean causation and should be evaluated carefully. All physiological variables were tested for correlation and only the statistically significant values are displayed on Table 27.

Table 27. Event-based results of pupil – Between groups

Variable 1	Variable 2	Pearson (r)	Sig. (2-tailed)
EDA	1st Derivative EDA valgus	0.516	**0.014***
EDA Alignment	Pupil 2 alignment	-0.757	**0.030***
EDA Alignment	Pupil 1 alignment	-0.750	**0.032***
1st Derivative EDA Varus	Pupil 2 alignment	0.828	**0.021***
1st Derivative 2 Alignment	HR Valgus	0.600	**0.011***

* $p < 0.05$

The results showed positive correlation between EDA and 1st derivative of valgus. The derivatives are useful because they detect true events of EDA. This result is an indication that there were true EDA events for valgus alignment, and they follow the pattern of the mean of the EDA signals.

There was also a negative correlation between EDA and pupil when both aligned. This result showed that as participants align both legs, the EDA response increases and pupil diameter decreases. This is an interesting result and may indicate a less stressful state after aligning both legs. Physiologically, this is supported by literature as they are both controlled by the sympathetic nervous system, which is responsible for involuntary responses to dangerous and stressful situations [187, 188].

Another result showed a negative correlation between EDA and pupil when one leg is aligned. This result exposes that as participant align one leg, the EDA response increases and pupil diameter decreases. This result also agrees with the correlation above as these are involuntary responses to stress or relaxation.

Another negative correlation was found between 1st derivative of varus and pupil when 2 aligned. This result exposes that as participant align both legs, the EDA response increases and pupil diameter decreases. Derivatives filters EDA events.

The last negative correlation was found between 1st derivative for full alignment and HR when in Valgus. This result exposes that as participant align both legs, the HR response decreases it is possible to detect EDA events. The literature reported similar correlations across different studies. Effects of heart rate, EDA, and pupil are linked to stressful situations and they are also related to arousal effects [222, 223].

5.8 Conclusion

This chapter presented a physiological-based QoE assessment of haptic and Augmented Reality feedback in a gait analysis system. It compared, in terms of physiological ratings, how users perceived and responded to Haptic and Augmented Reality feedback.

Event-based comparisons of range of heart rate showed higher variability for participants during haptic feedback, which can be an indicator of stress [189]. This variability was also reported in the male group. The haptic group also showed significant differences in electrodermal activity (EDA) for varus, partial alignment (only one leg aligned) and complete aligned (both legs aligned). This increase in EDA after feedback is a metric that was deeply analysed and reported in this chapter. The AR group showed significant difference for EDA for the same events (varus, partial alignment, and complete alignment). The male group did not demonstrate any difference in response when comparing both feedback modalities. There also significant results for frequency domain spectral analysis of event-based EDA, which detected the true EDA frequencies.

For the pupil diameter, a statistically significant difference was found between AR and haptic. When the participant received AR or haptic feedback and both legs were misaligned (varus or valgus), the pupil diameter was significantly smaller for the AR feedback, even though the participant received a visual-type feedback, which could mean that haptic feedback causes more stress in all participants. The results from pupil diameter also showed that as participants became misaligned (inefficient feedback), the pupil dilated significantly in the AR group. For the haptic feedback, more specifically in the female group, there was a significant pupil dilatation when participants were fully aligned.

There were correlations in the physiological measures such as derivatives of EDA, event-based EDA, and second derivatives. The results showed that EDA signals could be linked to pupil and heart variables to some extent. The correlations make sense as all physiological variables captured in this study are controlled by the sympathetic nervous system which is linked to rapid involuntary response to dangerous or stressful situations.

The next chapter concludes this dissertation and provides future work consideration and recommendations for the scientific community.

6 Conclusion and Future Work

This chapter presents the conclusion of the thesis and proposes possible directions for future research.

6.1 Conclusion

This key findings from this PhD thesis were the results from a QoE evaluation of haptic and AR feedback in a low-cost gait feedback system. The initial part of this PhD project focused on the low-cost gait system development and Motion Capture (MoCap) evaluation in human movement capture (3D joints), specifically focussing on the assessment of gait. The objective was to develop an alternative, cheaper and more accessible system based on the integration of a camera system and inertial sensors. A comparison of the low-cost system with a gold standard in motion capture, was performed and the developed marker-less system could not only replicate 3D joints and gait angles, but it could also present gait spatiotemporal variables. Based on this, many potential use cases of the gait system could be proposed, including integration with feedback modules.

At a system level, the proposed system is a cheaper alternative. The price of the low-cost system was less than 5% of the cost of VICON which cost approximately 200.000 € [224]. The system provides clear and easily interpretable results; supports 360 degrees of motion analysis; is easily portable; and does not require large set up space or environment. From the gait perspective, the system was capable of measuring gait angles of knee and hip with 95% bootstrap confidence interval, when compared to the gold standard. Spatiotemporal results showed similarity with significant results of 99% on gait cycle time (s), 95% on right stride time (s), 90% on left stride time (s), 88% on gait length (m), 95% on stride length (m), and 91% on gait velocity (m/s).

Considering the hardware requirements for this project to address varus/valgus alignment, it was decided to only use IMUs for the gait feedback application. In this way, the range of the system would be increased, and the system would be even more portable.

The second part of the project has focused on evaluating QoE of the different gait feedback modalities: AR and haptic. The feedback aimed to reduce knee varus and valgus misalignments, which can cause serious orthopaedics problems, such as osteoarthritis and injuries [25, 30, 167]. Despite current feedback modalities such as 2D screens, audio, expert guidance are widely used for some applications, there are opportunities in applying immersive technologies such as AR feedback in gait. Results of the QoE evaluation of AR and Haptic feedback were presented considering explicit (questionnaires), implicit (physiological) and objective metrics and correlation analysis.

Objective results revealed that participants performed better with AR feedback, with a reduction of 31% for varus and 13% for valgus. The male improved for varus (45% $p = 0.034$) and valgus (18% $p = 0.073$) while females did not have significant improvement.

Explicit results of questionnaires have demonstrated that the novel AR feedback not only provided better performance in reducing misalignments, but it also showed less physical demand when compared to haptic. Participants felt the adjustment was easier with AR when compared to haptic. This was similar reported in the female group.

Implicit physiological measures of participants were also presented. Event-based comparisons of range of heart rate showed higher variability for participants during haptic feedback, which is an indicator of stress and was also reported in the male group. There was no statistically significant difference in the AR group.

The haptic and AR groups also showed significant differences in electrodermal activity (EDA) for varus, partial alignment (only one leg aligned) and complete aligned (both legs aligned), which are indicative of increased stress. True EDA signals were filtered through frequency analysis. Pupil analysis showed that whenever the participant received AR or haptic feedback and both legs were misaligned (varus or valgus), the pupil diameter was significantly smaller for the AR group. The final achievements dealt with bivariate correlations for physiological measures, which were important as they were linked to sympathetic nervous responses, which are linked to involuntary response to stressful situations and they are also related to arousal effects. The literature reported similar correlations across different studies [222, 223]. This gives a contribution for the work as there was no other work to date that reported a physiological report of gait and gait feedback. A summary of the QoE evaluation is presented on Table 28.

Table 28. QoE Summary for Haptic vs. Augmented Reality (AR) Feedback

Metric	Variable	Within Groups		Between Groups	
		Haptic	AR	Haptic	AR
Number of Misalignment	Varus Reduction	15%	**31% ***	**-**	**-**
	Valgus Reduction	9%	13%	-	-
	Total Misalignments	12%	**22% ***	-	-
Misalignment reduction	Time on Varus (s)	-21%	11%	-	-
	Time on Valgus (s)	-10%	**64% ***	**-**	**-**
	Total Misalignments Time (s)	-4%	**37% ***	**-**	**-**
MOS (0-7)	MOS (Q1)			**3.5***	**4.45***
	MOS (QoEM)			4.24	4.44
NASA-TLX	Physical Demand			**151.87***	**71.45***
SAM	VAD			-	-
HRV (IBI)	Mean	0.04	0.05	0.74	0.75
	SDNN	-0.03	0.03	0.06	0.09
	RMSSD	-0.01	0.02	0.08	0.11
HRV (HR)	Mean	-	-	-1.88	-0.30
	Range	-	-	-2.60	11.46
	Mean Varus	-	-	-3.85	0.883
	Range Varus	-	-	-7.53	-0.98
	Mean Valgus	-	-	-4.99	-5.80
	Range Valgus	-	-	-7.54	1.11
	Mean Alignment	-	-	-3.51	2.42
	Range Alignment	-	-	**-5.27 ***	**4.87 ***
EDA (Time-domain)	Mean	**0.15***	0.17	0.74	0.75
	1st Derivative	0.00	0.00	0.06	0.09
	2nd Derivative	0.00	0.00	0.08	0.11
	Mean Valgus	**0.14***	**0.05***	0.06	0.24
	Mean Varus	0.06	0.24	0.14	0.05
	Mean Alignment	**0.15***	**0.11***	0.15	0.11
EDA (Frequency-domain)	F0SC (0.05-0.1hz)	✓	-	-	-
	F1SC (0.1-0.2hz)	✓	-	-	-
	F2SC (0.2-0.3hz)	✓	-	-	-
	F3SC (0.3-0.4hz)	-	-	-	-
Pupil (z-scores)	Varus/Valgus	-0.01	-0.01	**0.18***	**-0.10***
	Alignment	-0.004	-0.004	-0.002	0.003
Pupil (Event-based)	Varus/Valgus to 1 alignment	-0.247	-0.247	**-0.09**	**0.15**
	1 alignment to Varus/Valgus	0.24	0.24	0.14	-0.09
	Full alignment to 1 leg aligned	0.15	0.15	0.064	-0.089
	1 Leg Aligned to full alignment	-0.146	-0.146	-0.123	0.023

***** $p < 0.05$; **-** No interaction effect.

In summary, this project closes a QoE study considering the development of a full gait system (hardware and software), and evaluation considering explicit and implicit measures of gait. It also reported physiological measures of heart, skin conductance, and pupil. Future work will include novel QoE methodologies and applications, the use of learning algorithms, and clinical studies.

6.2 Reflection of Research Questions

The proposed research question for this PhD work: *"What type of feedback, considering haptic and AR, supports the highest QoE in a low-cost gait analysis system?"* was addressed with both literature and the outlined studies. It was concluded that overall, the AR feedback supported highest QoE in the gait feedback system. The sub research questions of this project were also answered.

SubRQ1: "*Can we objectively and accurately evaluate gait performance in a low-cost gait analysis system?"*

This question was addressed by the initial comparison of the gait system with VICON. The gait capturing system was capable not only of evaluating gait angles and spatiotemporal variables, but it showed very accurate results when compared to the gold standard VICON.

SubRQ2: "*What do users self-report when experiencing different feedback systems in terms of key aspects such as experience and effort?"*

This question was partially addressed with support of the literature and with the QoE studies with participants. Post-test questionnaires were used to subjectively evaluate QoE. The AR feedback promoted highest QoE in this study. The NASA-TLX resulted in significantly higher physical demand for haptic feedback. There was no difference in emotion responses for both groups as they both reported high arousal, valence, and dominance.

SubRQ3: "*Can physiological measurements support a better understanding of user's response in the context of a QoE evaluation in a gait feedback system?"*

Another contribution of this work was at physiological level. Measures of heart, skin conductance and pupil were captured and showed differences for AR and haptic feedback. The pupil became significantly relaxed after a complete alignment with the AR feedback. Measures of heart and skin were observed in the haptic group, which could indicate a stressful condition due to autonomic nervous system responses.

SubRQ4: *"What type of feedback does user understand better during walk? Haptic or Augmented Reality feedback?"*

This question was addressed by the objective analysis of gait. AR feedback was the only feedback that could not only reduce the number of misalignments, but also reduced the time participants stayed in a misaligned state. This question was also addressed with the self-reported responses. Questionnaires reported less physical demand of AR when compared to haptic. Participants also felt the adjustment was easier with AR when compared to haptic.

SubRQ5: *"Can gender influence user's QoE in a gait feedback system?"*

With the gender analysis, it was possible to have some understanding of how females and males processed information for this study. It is well known by the literature that females and male have anatomical differences that could directly influence varus and valgus misalignments [26, 27, 117]. It was possible to conclude that gender is an influence factor of QoE in gait feedback, which can lead to further studies with this topic.

6.3 Limitations

The limitations of this study include hardware considerations, the objective variables of gait and feedback, QoE modelling, and some statistical considerations.

Considering hardware limitations, the Microsoft Kinect sensor used in the first study was discontinued. Even though the sensor is not being produced, there are currently many other alternatives such as the Azure Kinect, Intel RealSense, and Orbbec Astra [225]. However, this limitation did not affect the development of this projection as the developed algorithms can be used in any depth sensor alternative mentioned above. Another hardware limitation is the type of AR glasses used. New, and more ergonomic AR glasses are constantly developed. The test could also be done with some of the new glasses to improve further the user experience.

From a gait capturing perspective, the study could also be done with different variables of gait for feedback such as hip, trunk, and ankle angles. Although the advantages of using other variables as feedback input, it would be outside the scope of this project and can also be implemented as future contribution. Even though this limitation can be questioned, the gait IMU system has proven to capture gait angles in any anatomical plane.

A limitation from the feedback perspective would include the need of an adaptive feedback that takes into consideration individual inputs from user (e.g. individual values of feedback, anthropometric variables, and learning algorithms). In this way, the feedback would be more individual, hence, the improving the possibility of better performance and the quality of rehabilitation. However, this study has shown the capabilities of AR feedback, and even its limitation. Refined algorithms can also be used in clinical studies as part of the future work.

Finally, from a QoE perspective, this study could include further analysis to try to understand deeper the differences at cognitive level of males and females. Another contribution would be the development of QoE models for gait feedback and the use of inferential statistics to extend the sample outputs results into a population to evaluate the possibility of clinical QoE studies.

6.4 Future Work

There are many potential directions for this work. Looking at QoE analysis, several studies using the female population, which is a target population for knee misalignments can be performed. Another QoE contribution can be the detection of workload, stress, even emotion using machine learning classifiers and physiological measures [226, 227]. The QoE study of long-term interventions can also be a future study. In this manner, progression of the participant’s alignment can be observed, which can lead to applications in a clinical population.

There are also opportunities to apply deep learning algorithms such as classifiers to detect gait abnormalities and develop refined feedback methodologies for rehabilitation. In this way, long term interventions assessing changes in gait over time can be done. Another intervention can be to assess gait feedback at higher speeds and applications in sports such as sprint and smart gyms [228]. This research direction creates opportunities to collaboration with sports research centres, and the development of smart applications towards health, sports education, and rehabilitation.

Other examples include the use of feedback for clinical studies [229-231]. It is known that traditional rehabilitation approaches rely on the expert guidance [8, 23, 97]. Another possible contribution for this project is to clinically assess clinical participants such as potential knee replacement patients, and to evaluate post-surgery recovery [232]. This can be an application of the system to aid physiotherapists and clinicians with feedback outputs.

All these topics can be part of the natural progression of this work. My aim is to continue exploring the capabilities of motion capture and immersive technologies with a deeper understanding of user centred QoE research.

References

[1] J. G. Richards, "The measurement of human motion: A comparison of," *Human Movement Science*, vol. 18, pp. 589-602, 1999.

[2] A. V. S. Ferreira *et al.*, "Comparison of motor function in patients with Duchenne muscular dystrophy in physical therapy in and out of water: 2-year follow-up," *Acta Fisiatrica*, vol. 22, no. 2, pp. 51-54, 2015.

[3] K. Shivesh, "Contribution to modeling of human walking gait cycle over stride based on robotics for pedestrian navigation solution," ed. Nantes: Ecole Centrale de Nantes, 2015.

[4] S. Bennour, B. Ulrich, T. Legrand, B. Jolles, and J. Favre, *A gait retraining system using augmented-reality to modify footprint parameters: Effects on lower-limb sagittal-plane kinematics*. 2017.

[5] G. F. Harris and J. J. Wertsch, "Procedures for gait analysis," *Archives of Physical Medicine and Rehabilitation*, vol. 75, no. 2, pp. 216-225, 1994, doi: 10.5555/uri:pii:0003999394903999.

[6] L. S. Figueiredo, H. Ugrinowitsch, A. B. Freire, J. B. Shea, and R. N. Benda, "External Control of Knowledge of Results: Learner Involvement Enhances Motor Skill Transfer," *Perceptual and Motor Skills*, vol. 125, no. 2, pp. 400-416, 2018, doi: 10.1177/0031512517753503.

[7] A. A. Jafarnezhadgero, M. Majlesi, H. Etemadi, and D. G. E. Robertson, "Rehabilitation improves walking kinematics in children with a knee varus: Randomized controlled trial," *Annals of Physical and Rehabilitation Medicine*, vol. 61, no. 3, pp. 125-134, 2018/05/01/ 2018, doi: https://doi.org/10.1016/j.rehab.2018.01.007.

[8] K. Carr, N. Zachariah, P. Weir, and N. McNevin, *An Examination of Feedback Use in Rehabilitation Settings*. 2011, pp. 147-160.

[9] A. Ahrens, K. D. Lund, M. Marschall, and T. Dau, "Sound source localization with varying amount of visual information in virtual reality," *PLOS ONE*, vol. 14, no. 3, p. e0214603, 2019, doi: 10.1371/journal.pone.0214603.

[10] D. Hartanto, I. L. Kampmann, N. Morina, P. G. M. Emmelkamp, M. A. Neerincx, and W.-P. Brinkman, "Controlling Social Stress in Virtual Reality Environments," *PLOS ONE*, vol. 9, no. 3, p. e92804, 2014, doi: 10.1371/journal.pone.0092804.

[11] C. E. Stepp, Q. An, and Y. Matsuoka, "Repeated Training with Augmentative Vibrotactile Feedback Increases Object Manipulation Performance," *PLOS ONE*, vol. 7, no. 2, p. e32743, 2012, doi: 10.1371/journal.pone.0032743.

[12] T. Minh Vu, N. Katushin, and J. Pumwa, "Motion tracking glove for augmented reality and virtual reality," in *Paladyn, Journal of Behavioral Robotics* vol. 10, ed, 2019, p. 160.

[13] K. Brunnström *et al.*, *Qualinet White Paper on Definitions of Quality of Experience*. 2013.

[14] W. Robitza *et al.*, "Challenges of future multimedia QoE monitoring for internet service providers," *Multimedia Tools and Applications*, vol. 76, no. 21, pp. 22243-22266, 2017/11/01 2017, doi: 10.1007/s11042-017-4870-z.

[15] N. Murray, B. Lee, Y. Qiao, and G. Miro-Muntean, "The Impact of Scent Type on Olfaction-Enhanced Multimedia Quality of Experience," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 47, no. 9, pp. 2503-2515, 2017, doi: 10.1109/TSMC.2016.2531654.

[16] A. Floris and L. Atzori, "Quality of Experience in the Multimedia Internet of Things: Definition and practical use-cases," in *2015 IEEE International Conference on Communication Workshop (ICCW)*, 8-12 June 2015 2015, pp. 1747-1752, doi: 10.1109/ICCW.2015.7247433.

[17] M. Martini, C.-W. Chen, Z. Chen, T. Dagiuklas, L. Sun, and X. Zhu, *QoE-Aware Wireless Multimedia Systems*. 2012, pp. 1153-1156.

[18] J. Lei, Q. Zhu, J. Wu, and R. Xiong, "Gait analysis of human locomotion based on motion capture system," in *2014 IEEE 9th Conference on Industrial Electronics and Applications (ICIEA)*, Hangzhou, 2014.

[19] D. Kobsar, S. T. Osis, B. A. Hettinga, and R. Ferber, "Gait Biomechanics and Patient-Reported Function as Predictors of Response to a Hip Strengthening Exercise Intervention in Patients with Knee Osteoarthritis," *PLoS ONE*, vol. 10, no. 10, 2015.

[20] D. RB, "Reflections on clinical gait analysis," *J Electromyogr Kinesiol*, vol. 7, no. 4, pp. 251-257, 1997.

[21] D. Sutherland, "The evolution of clinical gait analysis part III--kinetics and energy assessment.," *Gait Posture*, vol. 4, pp. 447-461, 2005.

[22] A. Kharb, V. Saini, Y. Jain, and S. Dhiman, "A Review of Gait Cycle and its Parameters," *International Journal of Computational Engineering & Management*, vol. 13, no. 78-83, 2011.

[23] S. Krishnan, A. Dawood, R. Richards, J. Henckel, and A. Hart, "A review of rapid prototyped surgical guides for patient-specific total knee replacement," *The Bone and Joint Journal*, vol. 94-B, no. 11, pp. 1457-1461, 2012.

[24] B. Monaghan, T. Grant, W. Hing, and T. Cusack, "Functional exercise after total hip replacement (FEATHER) a randomised control trial," *BMC Musculoskeletal Disorders*, vol. 13, no. 237, 2012.

[25] L. Sharma *et al.*, "Varus and valgus alignment and incident and progressive knee osteoarthritis," (in eng), *Annals of the rheumatic diseases,* vol. 69, no. 11, pp. 1940-1945, 2010, doi: 10.1136/ard.2010.129742.

[26] K. Tamari, P. Tinley, and K. Aoyagi, "Gender and age-related differences in axial alignment of the lower limb among healthy Japanese volunteers: comparative and correlation study," (in eng), *J Jpn Phys Ther Assoc,* vol. 6, no. 1, pp. 25-34, 2003, doi: 10.1298/jjpta.6.25.

[27] A. Chang *et al.*, "Frequency of varus and valgus thrust and factors associated with thrust presence in persons with or at higher risk of developing knee osteoarthritis," (in eng), *Arthritis Rheum,* vol. 62, no. 5, pp. 1403-1411, 2010, doi: 10.1002/art.27377.

[28] Y. Zhang and J. M. Jordan, "Epidemiology of osteoarthritis," (in eng), *Clin Geriatr Med,* vol. 26, no. 3, pp. 355-369, 2010, doi: 10.1016/j.cger.2010.03.001.

[29] P. Darin A. "Use of a medial unloader knee brace to alter knee alignment – implications for knee osteoarthritis treatment." EXSS IMPACT. https://uncexss.wordpress.com/2016/03/21/843 (accessed June 21, 2020).

[30] G. M. Freisinger *et al.*, "Relationships between varus-valgus laxity of the severely osteoarthritic knee and gait, instability, clinical performance, and function," (in eng), *Journal of orthopaedic research : official publication of the Orthopaedic Research Society,* vol. 35, no. 8, pp. 1644-1652, 2017, doi: 10.1002/jor.23447.

[31] A. Baudet *et al.*, "Cross-Talk Correction Method for Knee Kinematics in Gait Analysis Using Principal Component Analysis (PCA): A New Proposal," *PLOS ONE*, vol. 9, no. 7, p. e102098, 2014, doi: 10.1371/journal.pone.0102098.

[32] T. Andriacchi, L. Muendermann, S. Corazza, and A. Chaudhari, "A new era in the capture of human movement; markerless capture of human movement," *Journal of Biomechanics - J BIOMECH,* vol. 39, 12/31 2006, doi: 10.1016/S0021-9290(06)83680-8.

[33] T. P. Andriacchi and E. J. Alexander, "Studies of human locomotion: past, present and future," *J Biomech,* vol. 33, no. 10, pp. 1217-1224, 2000.

[34] E. Ceseracciu, Z. Sawacha, and C. Cobelli, "Comparison of Markerless and Marker-Based Motion Capture Technologies through Simultaneous Data Collection during Gait: Proof of Concept," *PLoS One,* vol. 9, no. 3, 2014.

[35] P. Eichelberger *et al.*, "Analysis of accuracy in optical motion capture – A protocol for laboratory setup evaluation," *Journal of Biomehanics,* vol. 49, pp. 2085-2088, 2016.

[36] Vicon, ed: Vicon Motion Systems Ltd.

[37] A. Pfister, A. West, S. Bronner, and A. Noah, "Comparative abilities of Microsoft Kinect and Vicon 3D motion capture for gait analysis," *Journal of medical engineering & technology*, vol. 38, pp. 1-7, 05/30 2014, doi: 10.3109/03091902.2014.909540.

[38] P. Merriaux, Y. Dupuis, R. Boutteau, P. Vasseur, and X. Savatier, "A Study of Vicon System Positioning Performance," *Sensors*, vol. 17, no. 1591, 2017.

[39] Microsoft, "Kinect for Xbox One," ed: Microsoft Corporation, 2015.

[40] S. L. Colyer, M. Evans, D. P. Cosker, and A. I. T. Salo, "A Review of the Evolution of Vision-Based Motion Analysis and the Integration of Advanced Computer Vision Methods Towards Developing a Markerless System," *Sports Medicine - Open*, vol. 4, no. 1, p. 24, 2018/06/05 2018, doi: 10.1186/s40798-018-0139-y.

[41] W. I. Sellers and E. Hirasaki, "Markerless 3D motion capture for animal locomotion studies," *Biology Open*, vol. 3, pp. 356-368, 2014.

[42] S. Schuon, C. Theobalt, J. Davis, and S. Thrun, "High-Quality Scanning Using Time-Of-Flight Depth Superresolution," in *IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, Anchorage, AK.

[43] M. T. C. b. W. You. "The Hardware of Kinect Sensor. ." https://maythecodebewithu.wordpress.com/2013/07/28/the-hardware-of-kinect-sensor (accessed June 21, 2020).

[44] G. Billie, "Microsoft Kinect Sensor Evaluation," NASA Technical Reports Server (NTRS), Albuquerque, NM, 2011.

[45] S. Li, L. Cui, C. Zhu, B. Li, N. Zhao, and T. Zhu, "Emotion recognition using Kinect motion capture data of human gaits," (in eng), *PeerJ*, vol. 4, pp. e2364-e2364, 2016, doi: 10.7717/peerj.2364.

[46] H. M. Hondori and M. Khademi, "A Review on Technical and Clinical Impact of Microsoft Kinect on Physical Therapy and Rehabilitation," *Journal of Medical Engineering*, 2014.

[47] S. Springer and G. Y. Seligmann, "Validity of the Kinect for Gait Assessment:," *Sensors*, vol. 16, no. 2, p. 194, 2016.

[48] S. Choppin, B. Lane, and J. Wheat, "The accuracy of the Microsoft Kinect in joint angle measurement," *Sports Technology*, vol. 7, no. 1-2, pp. 98-105, 2014.

[49] S. W. Shepperd, "Quaternion from rotation matrix. [four-parameter representation of coordinate transformation matrix," NASA, Ed., 1978: NASA Publisher. [Online]. Available: https://ntrs.nasa.gov/search.jsp?R=19780048191. [Online]. Available: https://ntrs.nasa.gov/search.jsp?R=19780048191

[50] K. Otte *et al.*, "Accuracy and Reliability of the Kinect Version 2 for Clinical Measurement of Motor Function," *PLOS ONE*, vol. 11, no. 11, p. e0166532, 2016, doi: 10.1371/journal.pone.0166532.

[51] F. Schlagenhauf, S. Sreeram, and W. Singhose, "Comparison of Kinect and Vicon Motion Capture of Upper-Body Joint Angle Tracking," in *2018 IEEE 14th International Conference on Control and Automation (ICCA)*, 12-15 June 2018 2018, pp. 674-679, doi: 10.1109/ICCA.2018.8444349.

[52] D. J. Geerse, B. H. Coolen, and M. Roerdink, "Kinematic Validation of a Multi-Kinect v2 Instrumented 10-Meter Walkway for Quantitative Gait Assessments," *PLOS ONE*, vol. 10, no. 10, p. e0139913, 2015, doi: 10.1371/journal.pone.0139913.

[53] J. Saboune and F. Charpillet, "Markerless Human Motion Tracking from a Single Camera Using Interval Particle Filtering," *International Journal on Artificial Intelligence Tools*, vol. 16, no. 4, pp. 593-609, 2007.

[54] M. Gabel, R. Gilad-Bachrach, E. Renshaw, and A. Schuster, "Full Body Gait Analysis with Kinect," in *34th Annual International Conference of the IEEE EMBS*, San Diego, 2012.

[55] R. A. Clark, K. J. Bower, B. F. Mentiplay, K. Paterson, and Y.-H. Pua, "Concurrent validity of the Microsoft Kinect for assessment of spatiotemporal gait variables," *J Biomech*, vol. 46, pp. 2722-2725, 2013.

[56] S. Systems, "Clincal 3DMA," ed: Stt Systems.

[57] B. Muller, W. Ilg, M. A. Giese, and N. Ludolph, "Validation of enhanced kinect sensor based motion capturing for gait assessment," *PLoS ONE*, vol. 12, no. 4, pp. 1-18, 2017.

[58] S. Patel, H. Park, P. Bonato, L. Chan, and M. Rodgers, "A review of wearable sensors and systems with application in rehabilitation," *Journal of NeuroEngineering and Rehabilitation*, pp. 9-21, 2012.

[59] Observer. "The Wearable Tech Industry Is Expected to Hit $54 Billion by 2023." https://observer.com/2019/08/wearable-tech-industry-hit-54-billion-by-2023/ (accessed 1 June, 2020).

[60] V. Kempe, *Inertial MEMS: Principles and Practice*. Cambridge: Cambridge University Press, 2011.

[61] N. Ahmad, R. A. R. Ghazilla, N. M. Khairi, and V. Kasi, "Reviews on Various Inertial Measurement Unit (IMU) Sensor Applications," *International Journal of Signal Processing Systems*, vol. 1, no. 2, pp. 256-262, 2013.

[62] J. Stober, L. Fishgold, and B. Kuipers, "Learning the sensorimotor structure of the foveated retina," in *EpiRob*, 2009.

[63] R. Mooney, G. Corley, A. Godfrey, L. R. Quinlan, and G. ÓLaighin, "Inertial Sensor Technology for Elite Swimming Performance Analysis: A Systematic Review.," *Sensors,* vol. 16, no. 1, 2016.

[64] D. Rodríguez-Martín, C. Pérez-López, A. SamàOrcID, J. Cabestany, and A. Català, "A Wearable Inertial Measurement Unit for Long-Term Monitoring in the Dependency Care Area.," *Sensors,* vol. 13, no. 10, pp. 14079-14104, 2013.

[65] W. Tao, T. Liu, R. Zheng, and H. Feng, "Gait Analysis Using Wearable Sensors," *Sensors,* vol. 12, no. 2, pp. 2255-2283, 2012.

[66] A. Ahmadi *et al.*, "Human gait monitoring using body-worn inertial sensors and kinematic modelling," in *2015 IEEE SENSORS*, Busan, 2015, pp. `1-4.

[67] H. Sveistrup, "Motor rehabilitation using virtual reality," *Journal of NeuroEngineering and Rehabilitation,* vol. 1, no. 10, 2004.

[68] G. Alankus, A. Lazar, M. May, and C. Kelleher, "Towards customizable games for stroke rehabilitation," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, Atlanta, 2010, pp. 2113-2122.

[69] D. V. Henri *et al.*, "The implementation of inertial sensors for the assessment of temporal parameters of gait in the knee arthroplasty population," *Clinical Biomechanics,* vol. 54, pp. 22-27, 2018.

[70] A. Ferrari, P. Ginis, M. Hardegger, F. Casamassima, L. Rocchi, and L. Chiari, "A Mobile Kalman-Filter Based Solution for the Real-Time Estimation of Spatio-Temporal Gait Parameters," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 24, no. 7, pp. 764-773, 2016.

[71] "The GAITRite standard," ed.

[72] A. Bó, M. Hayashibe, and P. Poignet, "Joint Angle Estimation in Rehabilitation with Inertial Sensors and its Integration with Kinect," *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference,* vol. 2011, pp. 3479-83, 08/01 2011, doi: 10.1109/IEMBS.2011.6090940.

[73] H. Mousavi Hondori, M. Khademi, and c. lopes, *Monitoring Intake Gestures using Sensor Fusion (Microsoft Kinect and Inertial Sensors) for Smart Home Tele-Rehab Setting*. 2012.

[74] S. Feng and R. Murray-Smith, *Fusing Kinect Sensor and Inertial Sensors with Multi-rate Kalman Filter*. 2014, pp. 2.3-2.3.

[75] K. Liu, C. Chen, R. Jafari, and N. Kehtarnavaz, "Fusion of Inertial and Depth Sensor Data for Robust Hand Gesture Recognition," *IEEE Sensors Journal,* vol. 14, 06/01 2014, doi: 10.1109/JSEN.2014.2306094.

[76] R. Sigrist, G. Rauter, R. Riener, and P. Wolf, "Augmented visual, auditory, haptic, and multimodal feedback in motor learning: A review," *Psychonomic*

Bulletin & Review, vol. 20, no. 1, pp. 21-53, 2013/02/01 2013, doi: 10.3758/s13423-012-0333-8.

[77] T. McDaniel, S. Krishna, D. Villanueva, and S. Panchanathan, "A haptic belt for vibrotactile communication," in *2010 IEEE International Symposium on Haptic Audio Visual Environments and Games*, 16-17 Oct. 2010 2010, pp. 1-2, doi: 10.1109/HAVE.2010.5623962.

[78] S. Krishna, S. Bala, T. McDaniel, S. McGuire, and S. Panchanathan, "VibroGlove: an assistive technology aid for conveying facial expressions," presented at the CHI '10 Extended Abstracts on Human Factors in Computing Systems, Atlanta, Georgia, USA, 2010. [Online]. Available: https://doi.org/10.1145/1753846.1754031.

[79] Seosensory. "Neosensory – Experience Sound as Touch and Gain New Awareness." https://neosensory.com/ (accessed June 21, 2020).

[80] D. Chen and J.-B. Chossat, *HaptiVec: Presenting Haptic Feedback Vectors in Handheld Controllers using Embedded Tactile Pin Arrays*. 2019.

[81] H. A. Sonar, A. P. Gerratt, S. P. Lacour, and J. Paik, "Closed-Loop Haptic Feedback Control Using a Self-Sensing Soft Pneumatic Actuator Skin," *Soft robotics*, 2019.

[82] J. v. d. Linden, E. Schoonderwaldt, and J. Bird, "Towards a real-time system for teaching novices correct violin bowing technique," in *2009 IEEE International Workshop on Haptic Audio visual Environments and Games*, 7-8 Nov. 2009 2009, pp. 81-86, doi: 10.1109/HAVE.2009.5356123.

[83] J. Lieberman and C. Breazeal, "TIKL: Development of a Wearable Vibrotactile Feedback Suit for Improved Human Motor Learning," *IEEE Transactions on Robotics*, vol. 23, no. 5, pp. 919-926, 2007, doi: 10.1109/TRO.2007.907481.

[84] J. Xu, U. H. Lee, T. Bao, Y. Huang, K. H. Sienko, and P. B. Shull, "Wearable sensing and haptic feedback research platform for gait retraining," in *2017 IEEE 14th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, 9-12 May 2017 2017, pp. 125-128, doi: 10.1109/BSN.2017.7936023.

[85] Y. Gaffary, B. L. Gouis, M. Marchal, F. Argelaguet, B. Arnaldi, and A. Lécuyer, "AR Feels "Softer" than VR: Haptic Perception of Stiffness in Augmented versus Virtual Reality," *IEEE Transactions on Visualization and Computer Graphics*, vol. 23, no. 11, pp. 2372-2377, 2017, doi: 10.1109/TVCG.2017.2735078.

[86] T. Koritnik, A. Koenig, T. Bajd, R. Riener, and M. Munih, *Comparison of visual and haptic feedback during training of lower extremities*. 2010, pp. 540-6.

[87] L. Kauhanen, T. Palomäki, P. Jylänki, F. Aloise, M. Nuttin, and J. d. R. Millan, *Haptic Feedback Compared with Visual Feedback for BCI*. 2006.

[88] L. Turchet, P. Burelli, and S. Serafin, "Haptic Feedback for Enhancing Realism of Walking Simulations," *IEEE Transactions on Haptics*, vol. 6, no. 1, pp. 35-45, 2013, doi: 10.1109/TOH.2012.51.

[89] P. Shull, K. Lurie, M. Shin, T. Besier, and M. Cutkosky, "Haptic gait retraining for knee osteoarthritis treatment," in *2010 IEEE Haptics Symposium*, 25-26 March 2010 2010, pp. 409-416, doi: 10.1109/HAPTIC.2010.5444625.

[90] K. L. Lurie, P. B. Shull, K. F. Nesbitt, and M. R. Cutkosky, "Informing haptic feedback design for gait retraining," in *2011 IEEE World Haptics Conference*, 21-24 June 2011 2011, pp. 19-24, doi: 10.1109/WHC.2011.5945455.

[91] DigiCapital. "Augmented, Virtual & Mixed Reality analytics platform, market reports, strategy consulting, investment banking: AR/VR data you can trust, analytics you can rely on." https://www.digi-capital.com/ (accessed.

[92] M. Sanchez-Vives and M. Slater, "From presence to consciousness through virtual reality," *Nature reviews. Neuroscience*, vol. 6, pp. 332-9, 05/01 2005, doi: 10.1038/nrn1651.

[93] K. Ahir, K. Govani, R. Gajera, and M. Shah, "Application on Virtual Reality for Enhanced Education Learning, Military Training and Sports," *Augmented Human Research*, vol. 5, no. 1, p. 7, 2019/11/29 2019, doi: 10.1007/s41133-019-0025-2.

[94] A. Colbert, N. Yee, and G. George, "The digital workforce and the workplace of the future," ed: Academy of Management Briarcliff Manor, NY, 2016.

[95] Oculus. "Oculus | VR Headsets & Equipment." https://www.oculus.com (accessed June 6, 2020).

[96] C. F. Durham and K. R. Alden, "Enhancing patient safety in nursing education through patient simulation," in *Patient safety and quality: An evidence-based handbook for nurses*: Agency for Healthcare Research and Quality (US), 2008.

[97] M. C. Howard, "A meta-analysis and systematic literature review of virtual reality rehabilitation programs," *Computers in Human Behavior*, vol. 70, pp. 317-327, 2017.

[98] J. Carmigniani, B. Furht, M. Anisetti, P. Ceravolo, E. Damiani, and M. Ivkovic, "Augmented reality technologies, systems and applications," *Multimedia tools and applications*, vol. 51, no. 1, pp. 341-377, 2011.

[99] S. R. R. Sanches, M. Oizumi, C. Oliveira, E. F. Damasceno, and A. C. Sementille, "Aspects of User Profiles That Can Improve Mobile Augmented Reality Usage," in *2017 19th Symposium on Virtual and Augmented Reality (SVR)*, 1-4 Nov. 2017 2017, pp. 236-242, doi: 10.1109/SVR.2017.38.

[100] P. A. Rauschnabel, A. Rossmann, and M. C. tom Dieck, "An adoption framework for mobile augmented reality games: The case of Pokémon Go," *Computers in Human Behavior*, vol. 76, pp. 276-286, 2017.

[101] P. Rauschnabel and Y. K. Ro, *Augmented Reality Smart Glasses: An Investigation of Technology Acceptance Drivers*. 2016, pp. 123-148.

[102] Epson. "Epson Moverio BT-300." Epson. https://moverio.epson.com/ (accessed 15, 2019).

[103] G. Nagymáté and R. M. Kiss, "Affordable gait analysis using augmented reality markers," *PLOS ONE,* vol. 14, no. 2, p. e0212319, 2019, doi: 10.1371/journal.pone.0212319.

[104] G. J. Diaz, M. S. Parade, S. L. Barton, and B. R. Fajen, "The pickup of visual information about size and location during approach to an obstacle," *PLOS ONE,* vol. 13, no. 2, p. e0192044, 2018, doi: 10.1371/journal.pone.0192044.

[105] J. Matthis, S. Barton, and B. Fajen, "The critical phase for visual control of human walking over complex terrain," *Proceedings of the National Academy of Sciences,* vol. 114, 07/24 2017, doi: 10.1073/pnas.1611699114.

[106] K. Binaee and G. J. Diaz, "Assessment of an augmented reality apparatus for the study of visually guided walking and obstacle crossing," *Behavior Research Methods,* vol. 51, no. 2, pp. 523-531, 2019/04/01 2019, doi: 10.3758/s13428-018-1105-9.

[107] R. Kothari, K. Binaee, J. S. Matthis, R. Bailey, and G. J. Diaz, "Novel apparatus for investigation of eye movements when walking in the presence of 3D projected obstacles," presented at the Proceedings of the Ninth Biennial ACM Symposium on Eye Tracking Research & Applications, Charleston, South Carolina, 2016.

[108] Y. A. Sekhavat and M. S. Namani, "Projection-Based AR: Effective Visual Feedback in Gait Rehabilitation," *IEEE Transactions on Human-Machine Systems*, vol. 48, no. 6, pp. 626-636, 2018, doi: 10.1109/THMS.2018.2860579.

[109] C.-H. Lee, Y. Kim, and B.-H. Lee, "Augmented reality-based postural control training improves gait function in patients with stroke: Randomized controlled trial," *Hong Kong Physiotherapy Journal*, vol. 32, no. 2, pp. 51-57, 2014/12/01/ 2014, doi: https://doi.org/10.1016/j.hkpj.2014.04.002.

[110] S. M. Dahlgaard-Park, *The SAGE encyclopedia of quality and the service economy*. SAGE Publications, 2015.

[111] N. Elassy, "The concepts of quality, quality assurance and quality enhancement," *Quality Assurance in Education,* vol. 23, no. 3, pp. 250-261, 2015.

[112] S. Möller and A. Raake, *Quality of Experience: Advanced Concepts, Applications and Methods*. 2014.

[113] T. Ebrahimi, "Quality of multimedia experience: past, present and futur," in *MM''09: Proceedings of the seventeen ACM international conference on Multimedia*, 2009.

[114] T. Haines, J. McBride, N. Triplett, J. Skinner, K. Fairbrother, and T. J. Kirby, "A comparison of men's and women's strength to body mass ratio and varus/valgus knee angle during jump landings," *Journal of sports sciences,* vol. 29, pp. 1435-42, 09/15 2011, doi: 10.1080/02640414.2011.599039.

[115] R. J. Schmitz *et al.*, "Varus/valgus and internal/external torsional knee joint stiffness differs between sexes," (in eng), *Am J Sports Med,* vol. 36, no. 7, pp. 1380-1388, 2008, doi: 10.1177/0363546508317411.

[116] K. A. Russell, R. M. Palmieri, S. M. Zinder, and C. D. Ingersoll, "Sex differences in valgus knee angle during a single-leg drop jump," (in eng), *J Athl Train,* vol. 41, no. 2, pp. 166-171, Apr-Jun 2006. [Online]. Available: https://www.ncbi.nlm.nih.gov/pubmed/16791301

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1472649/.

[117] C. E. Quatman and T. E. Hewett, "The anterior cruciate ligament injury controversy: is "valgus collapse" a sex-specific mechanism?," (in eng), *Br J Sports Med,* vol. 43, no. 5, pp. 328-335, 2009, doi: 10.1136/bjsm.2009.059139.

[118] C. Keighrey, R. Flynn, S. Murray, and N. Murray, "A QoE evaluation of immersive augmented and virtual reality speech & language assessment applications," in *2017 Ninth International Conference on Quality of Multimedia Experience (QoMEX)*, 31 May-2 June 2017 2017, pp. 1-6, doi: 10.1109/QoMEX.2017.7965656.

[119] L. Omelina, B. Bonnechère, S. Van Sint Jan, and B. Jansen, *Analyzing the quality of experience of computer games in rehabilitation: the therapist's perspective*. 2016, pp. 105-108.

[120] ITU-T, "Methods for the subjective assessment of video quality, audio quality and audiovisual quality of Internet video and distribution quality television in any environment," Telecomunication Standardization Sector of ITU, 2016.

[121] D. Egan, S. Brennan, J. Barrett, Y. Qiao, C. Timmerer, and N. Murray, "An evaluation of Heart Rate and ElectroDermal Activity as an objective QoE evaluation method for immersive virtual reality environments," in *2016 Eighth International Conference on Quality of Multimedia Experience (QoMEX)*, 6-8 June 2016 2016, pp. 1-6, doi: 10.1109/QoMEX.2016.7498964.

[122] T. Braga Rodrigues, C. Ó Catháin, N. E. O'Connor, and N. Murray, "A Quality of Experience assessment of haptic and augmented reality feedback modalities in a gait analysis system," *PLOS ONE,* vol. 15, no. 3, p. e0230570, 2020, doi: 10.1371/journal.pone.0230570.

[123] A.-N. Moldovan, I. Ghergulescu, and C. H. Muntean, "VQAMap: A novel mechanism for mapping objective video quality metrics to subjective MOS scale," *IEEE Transactions on Broadcasting,* vol. 62, no. 3, pp. 610-627, 2016.

[124] I. Hupont, J. Gracia, L. Sanagustín, and M. A. Gracia, "How do new visual immersive systems influence gaming QoE? A use case of serious gaming with Oculus Rift," in *2015 Seventh International Workshop on Quality of Multimedia Experience (QoMEX)*, 26-29 May 2015 2015, pp. 1-6, doi: 10.1109/QoMEX.2015.7148110.

[125] J. Lewis, *The Revised Mean Opinion Scale (MOS-R): Preliminary Psychometric Evaluation*. 2001.

[126] R. Harte *et al.*, "Human-Centered Design Study: Enhancing the Usability of a Mobile Phone App in an Integrated Falls Risk Detection System for Use by Older Adult Users," *JMIR Mhealth Uhealth*, vol. 5, no. 5, p. e71doi: 10.2196/mhealth.7046.

[127] P. Hoonakker *et al.*, "Measuring workload of ICU nurses with a questionnaire survey: the NASA Task Load Index (TLX)," *IIE Transactions on Healthcare Systems Engineering*, vol. 1, no. 2, pp. 131-143, 2011/04/01 2011, doi: 10.1080/19488300.2011.609524.

[128] T.-M. Bynion and M. Feldner, "Self-Assessment Manikin," 2017, pp. 1-3.

[129] E. Hynes, R. Flynn, B. Lee, and N. Murray, *A Quality of Experience Evaluation Comparing Augmented Reality and Paper Based Instruction for Complex Task Assistance*. 2019, pp. 1-6.

[130] G. Verma and U. S. Tiwary, "Affect Representation and Recognition in 3D Continuous Valence-Arousal-Dominance Space," *Multimedia Tools and Applications*, vol. 76, 11/27 2015, doi: 10.1007/s11042-015-3119-y.

[131] S. Hart, *Nasa-task load index (Nasa-TLX); 20 years later*. 2006.

[132] R. Gupta, H. J. Banville, and T. H. Falk, "Multimodal Physiological Quality-of-Experience Assessment of Text-to-Speech Systems," *IEEE Journal of Selected Topics in Signal Processing*, vol. 11, no. 1, pp. 22-26, 2017.

[133] R. Schatz, T. Hossfeld, L. Janowski, and S. Egger-Lampl, *From Packets to People: Quality of Experience as a New Measurement Challenge*. Berlin: Springer, 2013.

[134] C. Keighrey, R. Flynn, S. Murray, S. Brennan, and N. Murray, "Comparing User QoE via Physiological and Interaction Measurements of Immersive AR and VR Speech and Language Therapy Applications," in *Proceedings of the on Thematic Workshops of ACM Multimedia 2017*, Mountain View, 2017.

[135] A. Moldovan, I. Ghergulescu, S. Weibelzahl, and C. H. Muntean, "User-centered EEG-based multimedia quality assessment," in *2013 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB)*, 5-7 June 2013 2013, pp. 1-8, doi: 10.1109/BMSB.2013.6621743.

[136] I. Ghergulescu and C. H. Muntean, "A Novel Sensor-Based Methodology for Learner's Motivation Analysis in Game-Based Learning," *Interacting with Computers*, vol. 26, no. 4, pp. 305-320, 2014, doi: 10.1093/iwc/iwu013.

[137] U. Engelke, D. P. Darcy, G. H. Mulliken, S. Bosse, and M. G. Martini, "Psychophysiology-based QoE Assessment: A Survey," *MEASURING QOE FOR ADVANCED MEDIA TECHNOLOGIES AND SERVICES*, no. JSTSP SPECIAL ISSUE, 2016.

[138] Z. Jie and H.-J. Kim. (2013, January) User Feedback Oriented Quality of Experience Management Framework. *China Communications*.

[139] D. Bogusevschi, C. Muntean, and G.-M. Muntean, "Teaching and learning physics using 3D virtual learning environment: A case study of combined virtual reality and virtual laboratory in secondary school," *Journal of Computers in Mathematics and Science Teaching*, vol. 39, no. 1, pp. 5-18, 2020.

[140] I. Hupont, J. Gracia, L. Sanagustín, and M. A. Gracia, "How do new visual immersive systems influence gaming QoE? A use case of serious gaming with Oculus Rift," in *2015 Seventh International Workshop on Quality of Multimedia Experience (QoMEX)*, Pylos-Nestoras, 2015.

[141] W. Stiles, "Quality-Control in Qualitative Research," *Clinical Psychology Review*, vol. 13, pp. 593-618, 12/31 1993, doi: 10.1016/0272-7358(93)90048-Q.

[142] N. Zioulis *et al.*, "3D tele-immersion platform for interactive immersive experiences between remote users," in *2016 IEEE International Conference on Image Processing (ICIP)*, 25-28 Sept. 2016 2016, pp. 365-369.

[143] H. L. Mjøsund, E. Boyle, P. Kjaer, R. M. Mieritz, T. Skallgård, and P. Kent, "Clinically acceptable agreement between the ViMove wireless motion sensor system and the Vicon motion capture system when measuring lumbar region inclination motion in the sagittal and coronal planes," *BMC musculoskeletal disorders*, vol. 18, no. 1, p. 124, 2017.

[144] G. Zhao, G. Liu, H. Li, and M. Pietikainen, "3D gait recognition using multiple cameras," in *7th International Conference on Automatic Face and Gesture Recognition, 2006. FGR 2006.*, Southampton, 2006.

[145] M. Derlatka, "Human Gait Recognition Based on Signals from Two Force Plates," in *International Conference on Artificial Intelligence and Soft Computing*, Berlin, 2012.

[146] A. Castelli, G. Paolini, A. Cereatti, and U. Della Croce, "A 2D Markerless Gait Analysis Methodology: Validation on Healthy Subjects," *Computational and Mathematical Methods in Medicine*, vol. 2015, no. 186780, 2015.

[147] T. B Rodrigues, C. Ó Catháin, D. Devine, K. Moran, N. E. O'Connor, and N. Murray, "An Evaluation of a 3D Multimodal Marker-less Motion Analysis

System," in *ACM Multimedia Systems Conference 2019*, Amherst, MA, USA, ACM, Ed., 2019, doi: http://dx.doi.org/10.1145/3304109.3306236.

[148] M. Sebastian O. H., H. Andrew J. L., and V. Ravi, "Estimation of IMU and MARG orientation using a gradient descent algorithm," in *2011 IEEE International Conference on Rehabilitation Robotics*, Zurich, 2011.

[149] T. Wei, B. Lee, Y. Qiao, A. Kitsikidis, K. Dimitropoulos, and G. Nikos, *Experimental study of skeleton tracking abilities from microsoft kinect non-frontal views*. 2015.

[150] H. Berthold K. P., "Closed-form solution of absolute orientation using unit quaternions," *Journal of the Optical Society of America*, vol. 4, no. 4, pp. 629-642, 1987.

[151] Shimmer, "Shimmer3 IMU Unit," ed: © Shimmer.

[152] F. Stief, H. Böhm, K. Michel, A. Schwirtz, and L. Döderlein, "Reliability and Accuracy in Three-Dimensional Gait Analysis: A Comparison of Two Lower Body Protocols," *Journal of applied biomechanics*, vol. 29, pp. 105-111, 02/01 2013, doi: 10.1123/jab.29.1.105.

[153] H. Kainz *et al.*, "Reliability of four models for clinical gait analysis," *Gait & Posture*, vol. 54, 04/01 2017, doi: 10.1016/j.gaitpost.2017.04.001.

[154] A. Ferrari *et al.*, "Quantitative comparison of five current protocols in gait analysis," *Gait & posture*, vol. 28, pp. 207-16, 09/01 2008, doi: 10.1016/j.gaitpost.2007.11.009.

[155] "Plug-in Gait Reference Guide," ed: Vicon Motion Systems, 2018.

[156] L. S. Vargas-Valencia, A. Elias, E. Rocon, T. Bastos-Filho, and A. Frizera, "An IMU-to-Body Alignment Method Applied to Human Gait Analysis," (in eng), *Sensors (Basel)*, vol. 16, no. 12, p. 2090, 2016, doi: 10.3390/s16122090.

[157] VICON, "Fill gaps in trial data," ed: Vicon Motion Systems, 2018.

[158] R. Keane and R. Adrian, "Theory of cross-correlation analysis of PIV images," *Applied Scientific Research*, vol. 49, pp. 191-215, 01/07 1992, doi: 10.1007/BF00384623.

[159] H. Abdi and L. J. Williams, "Principal component analysis," *WIREs Comput. Stat.*, vol. 2, no. 4, pp. 433–459, 2010, doi: 10.1002/wics.101.

[160] E. Lau, C. Cooper, D. Lam, V. Chan, K. Tsang, and S. A, "Factors Associated with Osteoarthritis of the Hip and Knee in Hong Kong Chinese: Obesity, Joint Injury, and Occupational Activities," *American Journal of Epidemiology*, vol. 152, no. 9, pp. 855-862, 2000.

[161] S. E. Calce, H. K. Kurki, D. A. Weston, and L. Gould, "The relationship of age, activity, and body size on osteoarthritis in weight-bearing skeletal regions," *International Journal of Paleopathology*, vol. 22, pp. 45-53, 2018.

[162] U. Kujala, J. Kaprio, and S. Sarna, "Osteoarthritis of weight bearing joints of lower limbs in former elite male athletes," *BMJ: British Medical Journal*, vol. 308, no. 6923, pp. 231-234, 1994.

[163] A. Kale et al., "Identification of humans using gait," *EEE Transactions on Image Processing*, vol. 13, no. 9, pp. 1163-1173, 2004.

[164] A. Muro-de-la-Herran, B. Garcia-Zapirain, and A. Mendez-Zorrilla, "Gait Analysis Methods: An Overview of Wearable and Non-Wearable Systems, Highlighting Clinical Applications," *Sensors*, vol. 14, no. 2, pp. 3362–3394, 2014.

[165] V. C. Bacon-Shone and J. Bacon-Shone, "Gait of Normal Hong Kong Chinese Children: The Bootstrap Approach," *Hong Kong Physiotherapy Journal*, vol. 18, no. 1, pp. 21-25, 2000.

[166] M. W. Lenhoff, T. J. Santner, J. C. Otis, M. G. E. Peterson, B. J. Williams, and S. I. Backus, "Bootstrap prediction and confidence bands: a superior statistical method for analysis of gait data," *Gait and Posture*, vol. 9, pp. 10-17, 1999.

[167] R. Chaganti and N. Lane, "Risk factors for incident osteoarthritis of the hip and knee," *Current reviews in musculoskeletal medicine*, vol. 4, pp. 99-104, 08/02 2011, doi: 10.1007/s12178-011-9088-5.

[168] I. K. Center, "KMO and Bartlett’s Test," 2018.

[169] XSens. "Xsens | 3D Motion Tracking Technology." https://www.xsens.com/products/mtw-awinda/ (accessed.

[170] T. B. Rodrigues, D. P. Salgado, C. Ó. Catháin, N. O’Connor, and N. Murray, "Human gait assessment using a 3D marker-less multimodal motion capture system," *Multimedia Tools and Applications*, 2019/12/05 2019, doi: 10.1007/s11042-019-08275-9.

[171] V. Hu, E. Charry, M. Umer, A. Ronchi, and S. Taylor, *An inertial sensor system for measurements of tibia angle with applications to knee valgus/varus detection*. 2014, pp. 1-6.

[172] C. Liu, C. Ma, J. Zhou, L. Liu, S. Yue, and Q. Gong, "Feedback control for two-degree-of-freedom vibration system with fractional-order derivative damping," *Journal of Low Frequency Noise, Vibration and Active Control*, vol. 37, p. 146134841772595, 08/21 2017, doi: 10.1177/1461348417725958.

[173] S. Ryu, D. Pyo, S.-C. Lim, and D.-S. Kwon, "Mechanical Vibration Influences the Perception of Electrovibration," *Scientific Reports*, vol. 8, no. 1, p. 4555, 2018/03/14 2018, doi: 10.1038/s41598-018-22865-x.

[174] M. F. Rahman, D. Patterson, A. Cheok, and R. Betz, "30 - Motor Drives," in *Power Electronics Handbook (Fourth Edition)*, M. H. Rashid Ed.: Butterworth-Heinemann, 2018, pp. 945-1021.

[175] V. Bhatia, S. Joshi, and R. Chapaneri, "Websocket-Evented Real-Time Online Coding Collaborator," in *Smart Intelligent Computing and Applications*, Singapore, S. C. Satapathy, V. Bhateja, and S. Das, Eds., 2019// 2019: Springer Singapore, pp. 325-334.

[176] O. A Ilahi, N. R Kadakia, and M. Huo, "Inter- and intraobserver variability of radiographic measurements of knee alignment," *The American journal of knee surgery,* vol. 14, pp. 238-42, 02/01 2001.

[177] V. Borisov, G. Sprint, D. J. Cook, and D. L. Weeks, "Measuring Changes in Gait and Vehicle Transfer Ability During Inpatient Rehabilitation with Wearable Inertial Sensors," (in eng), *Proc IEEE Int Conf Pervasive Comput Commun Workshops,* vol. 2017, p. 10.1109/PERCOMW.2017.7917600, 2017, doi: 10.1109/PERCOMW.2017.7917600.

[178] N. Gregori, W. Feuer, and P. Rosenfeld, *Novel method for analyzing Snellen visual acuity measurements*. 2010, pp. 1046-50.

[179] R. W. Pickford, "The Ishihara Test for Colour Blindness," *Nature,* vol. 153, no. 3891, pp. 656-657, 1944/05/01 1944, doi: 10.1038/153656b0.

[180] J. A. Bell-Krotoski, E. E. Fess, J. H. Figarola, and D. Hiltz, "Threshold Detection and Semmes-Weinstein Monofilaments," *Journal of Hand Therapy,* vol. 8, no. 2, pp. 155-162, 1995/04/01/ 1995, doi: https://doi.org/10.1016/S0894-1130(12)80314-0.

[181] A. A. Laghari, H. Hui, M. Shafiq, and A. Khan, "Assessing effect of Cloud distance on end user's Quality of Experience (QoE)," in *2016 2nd IEEE International Conference on Computer and Communications (ICCC)*, 14-17 Oct. 2016 2016, pp. 500-505, doi: 10.1109/CompComm.2016.7924751.

[182] A. Bangor, P. T. Kortum, and J. T. Miller, "An Empirical Evaluation of the System Usability Scale," *International Journal of Human–Computer Interaction,* vol. 24, no. 6, pp. 574-594, 2008/07/29 2008, doi: 10.1080/10447310802205776.

[183] T. Schubert, F. Friedmann, and H. Regenbrecht, "The Experience of Presence: Factor Analytic Insights," *Presence: Teleoperators and Virtual Environments,* vol. 10, no. 3, pp. 266-281, 2001/06/01 2001, doi: 10.1162/105474601300343603.

[184] J. Lewis and J. R, *IBM Computer Usability Satisfaction Questionnaires: Psychometric Evaluation and Instructions for Use*. 1993, p. 57.

[185] P. Mishra, C. M. Pandey, U. Singh, A. Gupta, C. Sahu, and A. Keshri, "Descriptive statistics and normality tests for statistical data," (in eng), *Ann Card Anaesth,* vol. 22, no. 1, pp. 67-72, Jan-Mar 2019, doi: 10.4103/aca.ACA_157_18.

[186] A. Field, *Discovering Statistics using IBM SPSS Statistics*. Sage Publications Ltd., 2013, p. 952.

[187] H. F. Posada-Quintero, J. P. Florian, A. D. Orjuela-Cañón, and K. H. Chon, "Electrodermal Activity Is Sensitive to Cognitive Stress under Water," (in English), *Frontiers in Physiology,* Original Research vol. 8, no. 1128, 2018-January-17 2018, doi: 10.3389/fphys.2017.01128.

[188] R. Zangroniz, A. Martinez Rodrigo, J. M. Pastor García, M. López Bonal, and A. Fernández-Caballero, "Electrodermal Activity Sensor for Classification of Calm/Distress Condition," *Sensors,* vol. 17, p. 2324, 10/12 2017, doi: 10.3390/s17102324.

[189] H.-G. Kim, E.-J. Cheon, D.-S. Bai, Y. H. Lee, and B.-H. Koo, "Stress and Heart Rate Variability: A Meta-Analysis and Review of the Literature," (in eng), *Psychiatry Investig,* vol. 15, no. 3, pp. 235-245, 2018, doi: 10.30773/pi.2017.08.17.

[190] U. Engelke *et al.*, "Psychophysiology-Based QoE Assessment: A Survey," *IEEE Journal of Selected Topics in Signal Processing,* vol. PP, pp. 1-1, 09/15 2016, doi: 10.1109/JSTSP.2016.2609843.

[191] O. Faust, Y. Hagiwara, T. J. Hong, O. S. Lih, and U. R. Acharya, "Deep learning for healthcare applications based on physiological signals: A review," *Computer Methods and Programs in Biomedicine,* vol. 161, pp. 1-13, 2018/07/01/ 2018, doi: https://doi.org/10.1016/j.cmpb.2018.04.005.

[192] G. Chanel, A.-A. Karim, and P. Thierry, "Valence-arousal evaluation using physiological signals in an emotion recall paradigm," in *2007 IEEE International Conference on Systems, Man and Cybernetics*, 7-10 Oct. 2007 2007, pp. 2662-2667, doi: 10.1109/ICSMC.2007.4413638.

[193] P. Bonato, P. Boissy, U. Della Croce, and S. H. Roy, "Changes in the surface EMG signal and the biomechanics of motion during a repetitive lifting task," (in eng), *IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society,* vol. 10, no. 1, pp. 38-47, Mar 2002, doi: 10.1109/tnsre.2002.1021585.

[194] C. S. Klein, S. Li, X. Hu, and X. Li, "Editorial: Electromyography (EMG) Techniques for the Assessment and Rehabilitation of Motor Impairment Following Stroke," (in English), *Frontiers in Neurology,* Editorial vol. 9, no. 1122, 2018-December-18 2018, doi: 10.3389/fneur.2018.01122.

[195] Y. Nagano, H. Ida, M. Akai, and T. Fukubayashi, "Effects of jump and balance training on knee kinematics and electromyography of female basketball athletes during a single limb drop landing: pre-post intervention study," *Sports Medicine, Arthroscopy, Rehabilitation, Therapy & Technology,* vol. 3, no. 1, p. 14, 2011/07/14 2011, doi: 10.1186/1758-2555-3-14.

[196] L.-Q. Zhang, D. Xu, G. Wang, and R. W. Hendrix, *Muscle strength in knee varus and valgus*. 2001, pp. 1194-1199.

[197] D. B. Chaffin, M. Lee, and A. Freivalds, "Muscle strength assessment from EMG analysis," (in eng), *Medicine and science in sports and exercise,* vol. 12, no. 3, pp. 205-11, 1980.

[198] T. E. Hewett, B. T. Zazulak, G. D. Myer, and K. R. Ford, "A review of electromyographic activation levels, timing differences, and increased anterior cruciate ligament injury incidence in female athletes," (in eng), *Br J Sports Med,* vol. 39, no. 6, pp. 347-350, 2005, doi: 10.1136/bjsm.2005.018572.

[199] J. Donley, C. Ritz, and M. Shujau, *Analysing the Quality of Experience of Multisensory Media from Measurements of Physiological Responses*. 2014.

[200] S. Haiblum-Itskovitch, J. Czamanski-Cohen, and G. Galili, "Emotional Response and Changes in Heart Rate Variability Following Art-Making With Three Different Art Materials," (in eng), *Frontiers in psychology,* vol. 9, pp. 968-968, 2018, doi: 10.3389/fpsyg.2018.00968.

[201] Y. Wu, R. Gu, Q. Yang, and Y.-j. Luo, "How Do Amusement, Anger and Fear Influence Heart Rate and Heart Rate Variability?," (in English), *Frontiers in Neuroscience,* Original Research vol. 13, no. 1131, 2019-October-18 2019, doi: 10.3389/fnins.2019.01131.

[202] P. Jönsson, "Respiratory sinus arrhythmia as a function of state anxiety in healthy individuals," *International journal of psychophysiology,* vol. 63, no. 1, pp. 48-54, 2007.

[203] A. Lima *et al.*, "Walking capacity is positively related with heart rate variability in symptomatic peripheral artery disease," *European Journal of Vascular and Endovascular Surgery,* vol. 52, no. 1, pp. 82-89, 2016.

[204] F. Shaffer and J. P. Ginsberg, "An Overview of Heart Rate Variability Metrics and Norms," (in eng), *Front Public Health,* vol. 5, pp. 258-258, 2017, doi: 10.3389/fpubh.2017.00258.

[205] H. Posada-Quintero and K. Chon, "Innovations in Electrodermal Activity Data Collection and Signal Processing: A Systematic Review," *Sensors,* vol. 20, p. 479, 01/15 2020, doi: 10.3390/s20020479.

[206] C. M. Laine, K. M. Spitler, C. P. Mosher, and K. M. Gothard, "Behavioral triggers of skin conductance responses and their neural correlates in the primate amygdala," (in eng), *J Neurophysiol,* vol. 101, no. 4, pp. 1749-1754, 2009, doi: 10.1152/jn.91110.2008.

[207] E.-H. Jang, B.-J. Park, M.-S. Park, S.-H. Kim, and J.-H. Sohn, "Analysis of physiological signals for recognition of boredom, pain, and surprise emotions," (in eng), *J Physiol Anthropol,* vol. 34, no. 1, pp. 25-25, 2015, doi: 10.1186/s40101-015-0063-5.

[208] D. H. McDougal and P. D. Gamlin, "Autonomic control of the eye," (in eng), *Compr Physiol,* vol. 5, no. 1, pp. 439-473, 2015, doi: 10.1002/cphy.c140014.

[209] R. L. van den Brink, P. R. Murphy, and S. Nieuwenhuis, "Pupil Diameter Tracks Lapses of Attention," *PLOS ONE*, vol. 11, no. 10, p. e0165274, 2016, doi: 10.1371/journal.pone.0165274.

[210] E. Alexandridis and C. Baumann, "[Actual and apparent size of the pupil of the human eye]," (in ger), *Optica acta*, vol. 14, no. 3, pp. 311-6, Jul 1967, doi: 10.1080/713818034. Wirkliche und scheinbare Pupillenweiten des menschlichen Auges.

[211] D. Iacoviello, "Analysis of pupil fluctuations after a light stimulus by image processing and neural network," *Computers & Mathematics with applications*, vol. 53, no. 8, pp. 1260-1270, 2007.

[212] M. Bradley, L. Miccoli, M. Escrig, and P. Lang, "The pupil as a measure of emotional arousal and autonomic activation," *Psychophysiology*, vol. 45, pp. 602-7, 08/01 2008, doi: 10.1111/j.1469-8986.2008.00654.x.

[213] S. Schmitz, F. Krummenauer, S. Henn, and H. Dick, "Comparison of three different technologies for pupil diameter measurement," *Graefe's archive for clinical and experimental ophthalmology = Albrecht von Graefes Archiv für klinische und experimentelle Ophthalmologie*, vol. 241, pp. 472-7, 06/01 2003, doi: 10.1007/s00417-003-0669-x.

[214] E. Inc. "E4 wristband." https://e4.empatica.com/e4-wristband (accessed 2020).

[215] C. McCarthy, N. Pradhan, C. Redpath, and A. Adler, "Validation of the Empatica E4 wristband," in *2016 IEEE EMBS International Student Conference (ISC)*, 29-31 May 2016 2016, pp. 1-4.

[216] P. L. GmbH. "Pupil Labs: Add awareness to your VR/AR experience." https://pupil-labs.com/products/vr-ar/tech-specs/ (accessed.

[217] B. Ehinger, K. Groß, I. Ibs, and P. König, *A new comprehensive Eye-Tracking Test Battery concurrently evaluating the Pupil Labs Glasses and the EyeLink 1000*. 2019.

[218] J. Parák, A. Tarniceriu, P. Renevey, M. Bertschi, R. Delgado, and I. Korhonen, *Evaluation of the Beat-to-Beat Detection Accuracy of PulseOn Wearable Optical Heart Rate Monitor*. 2015.

[219] M. Davila, G. Lewis, and S. Porges, "The PhysioCam: A Novel Non-Contact Sensor to Measure Heart Rate Variability in Clinical and Field Applications," *Front Public Health*, vol. 5, 11/22 2017, doi: 10.3389/fpubh.2017.00300.

[220] J. Pietilä *et al.*, "Evaluation of the accuracy and reliability for photoplethysmography based heart rate and beat-to-beat detection during daily activities," Singapore, 2018: Springer Singapore, in EMBEC & NBC 2017, pp. 145-148.

[221] H. Posada-Quintero and K. Chon, *Frequency-domain electrodermal activity index of sympathetic function*. 2016, pp. 497-500.

[222] C.-A. Wang, T. Baird, J. Huang, J. D. Coutinho, D. C. Brien, and D. P. Munoz, "Arousal Effects on Pupil Size, Heart Rate, and Skin Conductance in an Emotional Face Task," (in eng), *Frontiers in neurology,* vol. 9, pp. 1029-1029, 2018, doi: 10.3389/fneur.2018.01029.

[223] P. Ren, A. Barreto, Y. Gao, and M. Adjouadi, "Comparison of the use of pupil diameter and galvanic skin response signals for affective assessment of computer users," *Biomedical sciences instrumentation,* vol. 48, pp. 345-50, 07/31 2012.

[224] A. Patrizi, E. Pennestri, and P. P. Valentini, *Comparison between low-cost marker-less and high-end marker-based motion capture systems for the computer-aided assessment of working ergonomics*. 2015, pp. 1-11.

[225] d. S. Expert. "3d Scanner Alternatives for Microsoft's Discontinued Kinect." https://3dscanexpert.com/alternatives-microsoft-discontinues-kinect-popular-low-cost-3d-scanner/ (accessed 16 June, 2020).

[226] V. Vasilev, J. Leguay, S. Paris, L. Maggi, and m. Debbah, *Predicting QoE Factors with Machine Learning*. 2018, pp. 1-6.

[227] P. Casas *et al.*, *Predicting QoE in cellular networks using machine learning and in-smartphone measurements*. 2017, pp. 1-6.

[228] A. Tadayon, T. McDaniel, and S. Panchanathan, "Functional Case Study Evaluation of the SmartGym: An Anticipatory System to Detect Body Compliance," presented at the Proceedings of the 3rd International Workshop on Multimedia for Personal Health and Health Care, Seoul, Republic of Korea, 2018. [Online]. Available: https://doi.org/10.1145/3264996.3265004.

[229] E. Halilaj, A. Rajagopal, M. Fiterau, J. L. Hicks, T. J. Hastie, and S. L. Delp, "Machine learning in human movement biomechanics: Best practices, common pitfalls, and new opportunities," (in eng), *J Biomech,* vol. 81, pp. 1-11, 2018, doi: 10.1016/j.jbiomech.2018.09.009.

[230] A. Baca, *Methods for recognition and classification of human motion patterns—A prerequisite for intelligent devices assisting in sports activities*. 2012, pp. 55-61.

[231] E. Dorschky, M. Nitschke, C. Martindale, A. van den Bogert, A. Koelewijn, and B. Eskofier, "CNN-based Estimation of Sagittal Plane Walking and Running Biomechanics from Measured and Simulated Inertial Sensor Data," 05/18 2020, doi: 10.3389/fbioe.2020.00604.

[232] V. Camomilla, E. Bergamini, S. Fantozzi, and G. Vannozzi, "Trends Supporting the In-Field Use of Wearable Inertial Sensors for Sport Performance Evaluation: A Systematic Review," (in eng), *Sensors (Basel),* vol. 18, no. 3, p. 873, 2018, doi: 10.3390/s18030873.

Appendix A – Participant Information Sheet

Participant Information Sheet

1. An Assessment of Microsoft Kinect for Motion Capture

Brief explanation of title: The purpose of this study is to evaluate the performance of Microsoft Kinect to measure human Gait. It will compare the accuracy of the MS Kinect system combined with Shimmer inertial sensors, against the VICON motion capture system (gold standard in motion analysis).

The Microsoft Kinect is a motion sensor developed for the Xbox 360 and Xbox One. It is resident in many homes around the world as a system used for gaming. It can track user's movement. It allows players to interact with video games without a joystick, innovating in the field of gameplay, hence it is completely non-invasive as no markers need to be placed on the human body – it estimates joint locations. Beside the gaming experience, the MS Kinect can be a powerful tool in human movement analysis, capturing biomechanical data like joint angles and velocity.

Shimmer is a non-invasive inertial sensor system that enables the capture, transmission, processing and display of body's data. Shimmer offers a flexible wireless sensor platform, scientifically reliable data and complete control of data capture, interpretation and analysis.

2. Introduction

I am inviting you to take part in a research study taking place in the School of Health and Human Performance in Dublin City University. The aim of this document is to explain why the research is being carried out and what it will involve. If you are not clear on any points, please do not hesitate to contact me. Thank you for reading this.

3. What is the purpose of the project?

We will compare the performance of the VICON motion capture system with the MS Kinect and Shimmer Sensors. We will evaluate gait parameters in healthy participants. In our project we are using the MS Kinect and Shimmer sensors as a motion capture system. Through gait analysis systems it is possible to evaluate the walking movement, see differences in joint angles, and compare with standard values.

In this study we aim to promote an assessment of your gait movements and evaluate the results. We are using the Microsoft Kinect to capture metadata (numbers), and through the Kinect depth camera we can estimate your joints evaluating your gait movement. We are also using the Shimmer device to estimate velocity, displacement, and angle.

4. Do I have to take part?

It is entirely up to you to decide whether you wish to take part in this study. Refusal to take part is entirely at your discretion. If you decide to take part, you can keep this information sheet and will be required to sign a consent form.

5. What does the experiment involve?

This experiment will be taken in a laboratory in the DCU. It should last maximum 30 minutes. It involves walking through a path of approximately 4 meters. This path is captured by Kinect and the Shimmer will capture the data. The lab will consist of a chair, a specific path (where you will be requested to walk), and a set of Microsoft Kinects.

6. What do I have to do?

You do not have to do anything before the testing. This is a non-invasive test. For the test you just need to walk through the path in your normal walking speed.

7. What are the possible disadvantages and risks of taking part?

There are no disadvantages and risk during this test.

8. Will my taking part in this project be kept confidential?

We will be capturing only metadata (numbers). The results of this experiment will be stored and any information collected during this test will be strictly confidential.

9. What will happen to the results of the research project?

The results of this experiment will be used to produce papers for publication as part of my research.

10. Thanks!

Just like to say, thank you very much for your time and help with this experiment.

Appendix B – Participant Consent Form

Centre Number:
Study Number:
Participant Identification Number:

CONSENT FORM

Title of Project: An Assessment of Microsoft Kinect for Motion Capture
Name of Researcher: Thiago Braga Rodrigues

Please initial box

1. I confirm that I have read the information sheet dated........................... (version...........) for the above study and have had the opportunity to ask questions. ☐

2. I am satisfied that I understand the information provided and have had enough time to consider the information. ☐

3. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason, without my legal rights being affected. ☐

4. I agree to take part in the above study. ☐

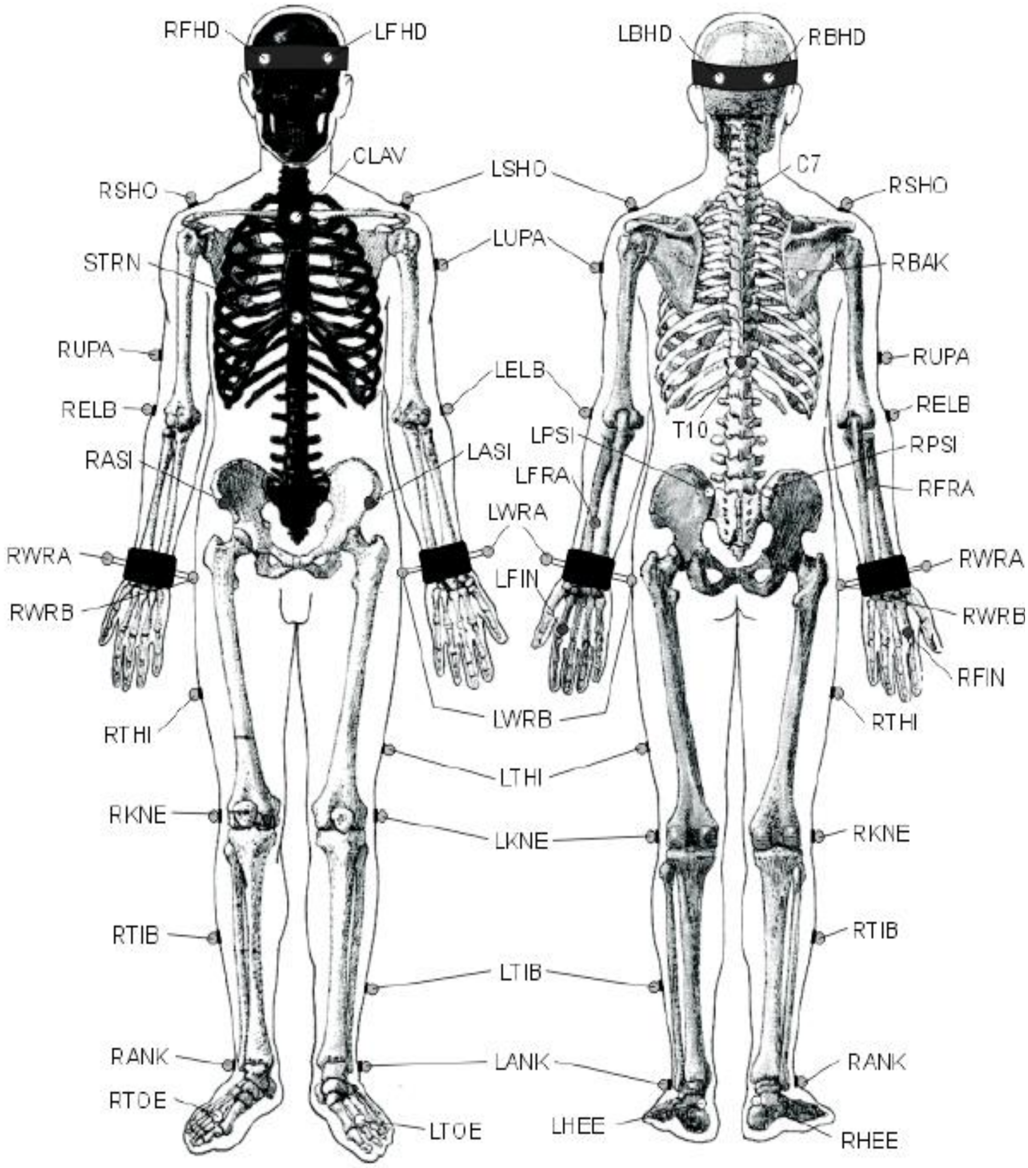
______________________	______________	__________________
Name of Participant	Date	Signature

______________________	______________	__________________
Name of Person taking consent (if different from researcher)	Date	Signature

______________________	______________	__________________
Researcher	Date	Signature

Appendix C – Plug-In-Gait Marker Placement

Plug-in-Gait Marker Placement



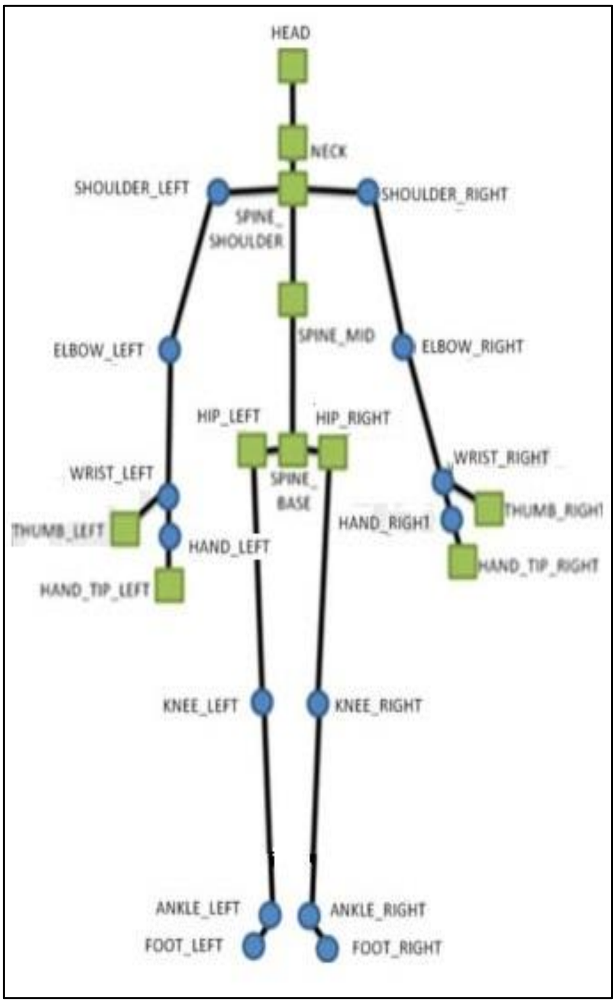
The following describes in detail where the Plug-in-Gait markers should be placed on the subject. Where left side markers only are listed, the positioning is identical for the right side.

Appendix D – Participant Measurements Sheet

Centre Number:
Study Number:
Participant Identification Number:

Participant Measurements

Title of Project: An Assessment of Microsoft Kinect for Motion Capture
Name of Researcher: Thiago Braga Rodrigues
Date:



MEASUREMENTS

Left / Right

1: Height _______

2: Weight _______

3: Hip - Hip _______

4: Hip – Ankle ______/_______

5: Hip – Knee ______/_______

6: Knee – Ankle ______/_______

7: Ankle – Foot ______/_______

8: Shoulder –Spine S ______/_______

1 – Take measurements while setting VICON markers
2 – Put Shimmers (1 – Spine S – 2 Spine Base – 3 – R Hip-Knee – 4 – R Knee Ankle)
3 – Movements:

a) Static Trial – 1 trial   Stand in the middle of sensors, Wait
b) Walk Trial – 8 trials   1 – Jump, 2 – Walk, 3 – Jump, 4 – Wait
c) Squat Trial – 2 Trials   8 Squats, Wait

Knee lifts – 2 Trials   8 knee lifts, Wait

Appendix E – IMU Algorithm

```
// This is a simplified algorithm to provide angles in any plane
using IMUS. Do not use this without authorization.
// Author: Thiago Braga Rodrigues

private void timer1_Tick(object sender, EventArgs e)
{

    int i_ori = 0;
    int i_qua = 0;
    double[,] _dcmQref = new double[3,1];
    string text = "";
    XsVector3 _datas;
    XsQuaternion _quaternion  = new XsQuaternion(0, 0, 0, 0);


    foreach (KeyValuePair<uint, ConnectedMtData> data in
_connectedMtwData)
    {

        if (data.Value._orientation != null)
        {

            _quaternion =
_quaternion.fromEulerAngles(data.Value._orientation);
          //  Console.WriteLine("[{0}]", string.Join(", ",
_quaternion.w()));

            array_qua[i_qua] = _quaternion.w();
            array_qua[i_qua + 1] = _quaternion.x();
            array_qua[i_qua + 2] = _quaternion.y();
            array_qua[i_qua + 3] = _quaternion.z();

            _datas = data.Value._calibratedData.m_acc;
            text += string.Format("...",
                                   data.Value._orientation.x(),
                                   data.Value._orientation.y(),
                                   data.Value._orientation.z(),
data.Key);
            array_ori[i_ori] = data.Value._orientation.x();
            array_ori[i_ori + 1] = data.Value._orientation.y();
            array_ori[i_ori + 2] = data.Value._orientation.z();

            _oriminuscal[i_ori] = array_ori[i_ori] -
_oricalibrated[i_ori];
            _oriminuscal[i_ori + 1] = array_ori[i_ori + 1] -
_oricalibrated[i_ori + 1];
            _oriminuscal[i_ori + 2] = array_ori[i_ori + 2] -
_oricalibrated[i_ori + 2];

            _accxyz[i_ori] = _datas.value(0);
            _accxyz[i_ori + 1] = _datas.value(1);
            _accxyz[i_ori + 2] = _datas.value(2);
        }
        i_ori += 3;
        i_qua += 4;
        //  _oriminuscal = array_ori - _oricalibrated;
```

```
    }

    _qref1.assign(array_qua[0], array_qua[1], array_qua[2],
array_qua[3]);      //Sensor 1
    // ... repeat

    _dcmQref1 = _DCMqua(_qref1);
    // ... repeat

    _Euler1[0, 0] = _oricalibrated[0];
    // ... repeat

    _Tibia1 = _EulerAnglesToMatrix(_Euler1, 1);
    _Tibia2 = _EulerAnglesToMatrix(_Euler2, 1);
    _Femur1 = _EulerAnglesToMatrix(_Euler3, 1);
    _Femur2 = _EulerAnglesToMatrix(_Euler4, 1);
    _Sacrum = _EulerAnglesToMatrix(_Euler5, 1);
    _Trunk  = _EulerAnglesToMatrix(_Euler6, 1);

    _result1 = _MultiplyMatrix(_dcmQref1, _Tibia1);
    // ... repeat

    // These are angles from the unit vectors
    _angle1 = _toDeg(Math.Atan(_result1[0, 1] / _result1[0, 0])); //
L sensor 1 Tibia angle plane XY
    _angle2 = _toDeg(Math.Atan(_result2[0, 1] / _result2[0, 0])); //
R sensor 2 Tibia angle plane XY

    _angle3 = _toDeg(Math.Atan(_result3[0, 2] / _result3[0, 0]) -
Math.Atan(_result1[0, 2] / _result1[0, 0])); // L sensor 3 angle
plane XZ
    _angle4 = _toDeg(Math.Atan(_result4[0, 2] / _result4[0, 0]) -
Math.Atan(_result2[0, 2] / _result2[0, 0])); // L sensor 3 angle
plane XZ

    _angle5 = _toDeg(Math.Atan(_result5[0, 2] / _result5[0, 0]) -
Math.Atan(_result3[0, 2] / _result3[0, 0])); // M sensor 5 angle
plane XZ
    _angle6 = _toDeg(Math.Atan(_result5[0, 2] / _result5[0, 0]) -
Math.Atan(_result4[0, 2] / _result4[0, 0])); // M sensor 5 angle
plane XZ

    _angle7 = _toDeg(Math.Atan(_result6[0, 2] / _result6[0, 0])); //
M sensor 6 angle       plane XZ

    _angle1A = _toDeg(Math.Atan(_result1[0, 2] / _result1[0, 0]));
    _angle2A = _toDeg(Math.Atan(_result2[0, 2] / _result2[0, 0]));


}
```

Appendix F – Participant Information Sheet

Information Sheet

1. **A Quality of Experience Evaluation of an Adaptive Multimodal Feedback System for Gait Analysis**

In this experiment, we aim to evaluate user quality of experience when using two feedback mechanisms for knee alignment: haptic and augmented reality using smart glasses. The haptic system is built in a way to give tactile sensation on the body position where the movement must be changed whilst the augmented reality glasses project objects to the wearer's field of view. The aim of the study is to determine whether a user's quality of experience is higher with haptic or augmented reality feedback.

2. **Introduction**

I am inviting you to take part in a research experiment to be carried out in the Software Research Institute in Athlone Institute of Technology. The aim of this document is to explain why the research is being carried out and what it will involve. If you are not clear on any points, please do not hesitate to contact me. Thank you for reading this.

3. **What is the purpose of the project?**

In this experiment we aim to promote an assessment of your knee alignment. You will be assessed through inertial information from wearable devices and feedback will be given in haptic and augmented way. You will be asked to fill out a questionnaire at the end of this experiment for a quality assessment.

To evaluate gait parameters, it is necessary to develop some tests using motion wearable devices. Through gait analysis systems it is possible to evaluate the walking movement, joint alignment and angles. Through feedback, it is possible to help users to change their knee alignment.

4. **Do I have to take part?**

It is entirely up to you to decide whether you wish to take part in this experiment. Refusal to take part is entirely at your discretion. If you decide to take part, you can keep this information sheet and will be required to sign a consent form.

5. **What does the experiment involve?**

This experiment will take place in laboratory (u212) in the AIT Engineering Building. It should last approx. 40 minutes. It involves walk in a normal pace on a treadmill while using some devices. The lab will consist of a treadmill, inertial sensors, AR glasses, and haptic device. The participant will be asked to fill out a questionnaire at the end of the testing to give their thought on the quality of experience.

6. **What do I have to do?**

On the day of the test, prior to realization, participants should not undertake physical exercise.

7. **What are the possible disadvantages and risks of taking part?**

There is no direct risk during this test. Risk of falling is minimal. Should a participant at any point feel any problem it is important to communicate this to the PI.

8. **Will my taking part in this project be kept confidential?**

This test will be recorded, and any information collected during this test will be strictly confidential. It will not be possible to recognise you from this experiment.

9. **What will happen to the results of the research project?**

The results of this experiment will be used to produce some papers for publication as part of my research.

10. **Thanks!**

Just like to say, thank you very much for your time and help with this experiment.

Appendix G – Participant Consent Form

Consent Form

Title of project: **A Quality of Experience Evaluation of an Adaptive Multimodal Feedback System for Gait Analysis**

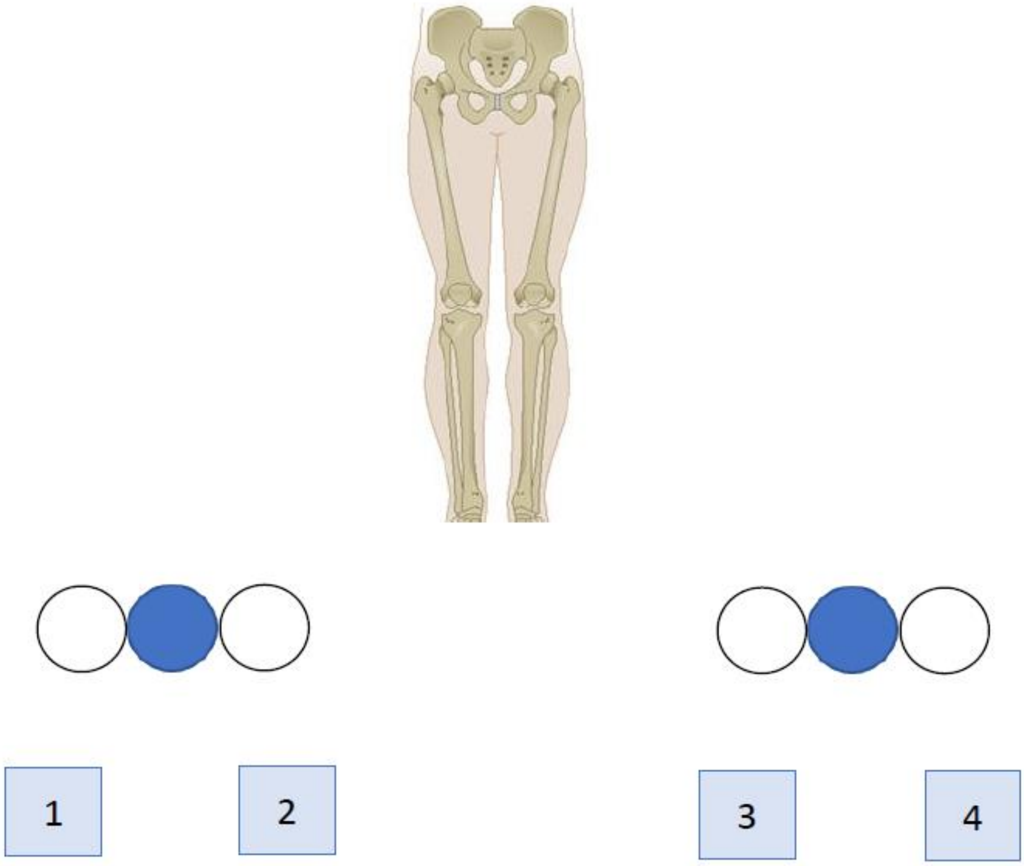
Principal Investigator**: Thiago Braga Rodrigues**

Please Tick the Box

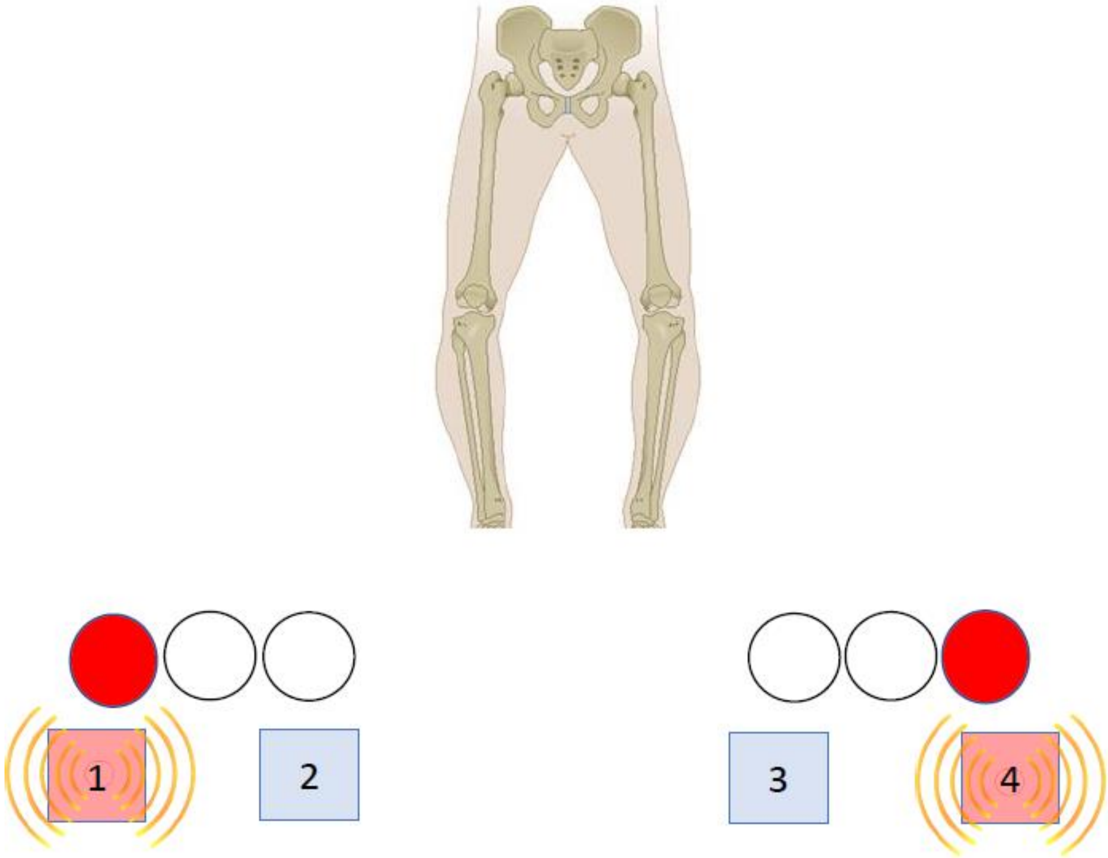
1. I am satisfied that I understand the information provided and have had enough time to consider the information. ☐
2. I do not suffer from photosensitive epilepsy or any other form of epilepsy. ☐
3. I'm not pregnant and/or I am not experiencing any symptoms of pregnancy. ☐
4. I have not consumed alcohol beverages for the last 24 hours. ☐
5. I slept at least 6 hours on last 24 hours. ☐
6. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason, without my legal rights being affected. ☐
7. I understand that any data collected in the course of this study will be used for research purpose only and in the strictest confidence. Any information related to me will be discarded at the completion of this research. ☐
8. I agree to take part in the above study. ☐
9. I confirm that I have read the information sheet dated ___/___/2018 for the above study and have had the opportunity to ask questions. ☐
10. Gender: Female ☐ Male ☐

________________________	________________	____________________
Name of Participant	Date	Signature
________________________	________________	____________________
Name of Person taking consent (if different from researcher)	Date	Signature
________________________	________________	____________________
Researcher	Date	Signature

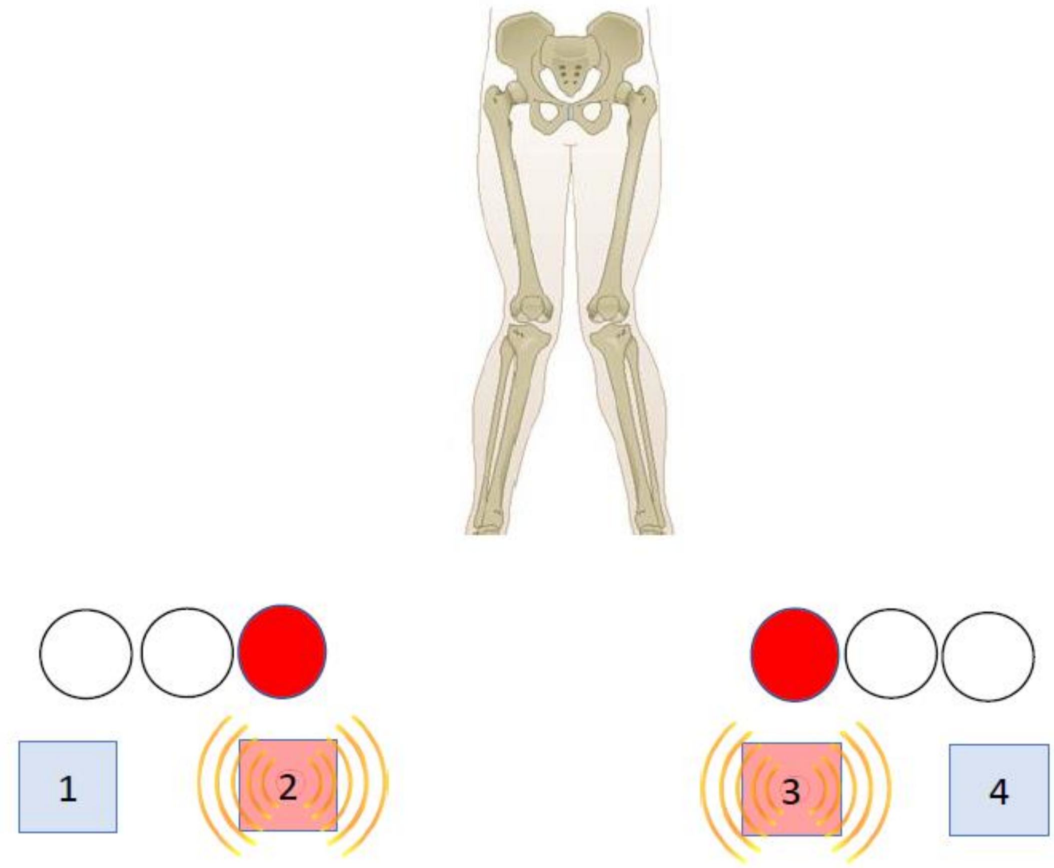
Appendix H – Feedback Explanation Sheets



Alignment (Text was not shown to participants)



Varus (Text was not shown to participants)



Valgus (Text was not shown to participants)

Appendix I – QoE Questionnaire

Subject ID: __Date: ____/___/___ **Gender:** F ☐ M ☐ **Feedback order:** 1 ☐ 2 ☐

Questionnaire – Part 1

Bellow, you will see statements regarding your experience from today. Please indicate, how each statement applies to your experience. Please remember: Read through statements to make sure you understand them. If you have any questions, please ask the assessor.

1. The feedback was clear.

Strongly agree	Agree	More or less agree	Undecided	More or less disagree	Disagree	Strong Disagree
①	②	③	④	⑤	⑥	⑦

2. I had to concentrate in order to understand what the system expected me to do.

Strongly agree	Agree	More or less agree	Undecided	More or less disagree	Disagree	Strong Disagree
①	②	③	④	⑤	⑥	⑦

3. The system provided constant feedback.

Strongly agree	Agree	More or less agree	Undecided	More or less disagree	Disagree	Strong Disagree
①	②	③	④	⑤	⑥	⑦

4. The feedback was easy to understand.

Strongly agree	Agree	More or less agree	Undecided	More or less disagree	Disagree	Strong Disagree
①	②	③	④	⑤	⑥	⑦

5. I needed to learn a lot of things before I could use the system.

Strongly agree	Agree	More or less agree	Undecided	More or less disagree	Disagree	Strong Disagree
①	②	③	④	⑤	⑥	⑦

6. The system was difficult to use.

Strongly agree	Agree	More or less agree	Undecided	More or less disagree	Disagree	Strong Disagree
①	②	③	④	⑤	⑥	⑦

7. I was aware of my body whilst moving.

Strongly agree	Agree	More or less agree	Undecided	More or less disagree	Disagree	Strong Disagree
①	②	③	④	⑤	⑥	⑦

8. I was aware of the real world surrounding while walking (e.g. sounds, room temperature, other people, etc.)?

Strongly agree	Agree	More or less agree	Undecided	More or less disagree	Disagree	Strong Disagree
①	②	③	④	⑤	⑥	⑦

9. I was not engaged with the system.

Strongly agree	Agree	More or less agree	Undecided	More or less disagree	Disagree	Strong Disagree
①	②	③	④	⑤	⑥	⑦

10. When I received feedback, I adjusted easily and quickly.

Strongly agree	Agree	More or less agree	Undecided	More or less disagree	Disagree	Strong Disagree
①	②	③	④	⑤	⑥	⑦

11. My walking style changed during experiment.

Strongly agree	Agree	More or less agree	Undecided	More or less disagree	Disagree	Strong Disagree
①	②	③	④	⑤	⑥	⑦

12. The system could not be used without the support of an expert.

Strongly agree	Agree	More or less agree	Undecided	More or less disagree	Disagree	Strong Disagree
①	②	③	④	⑤	⑥	⑦

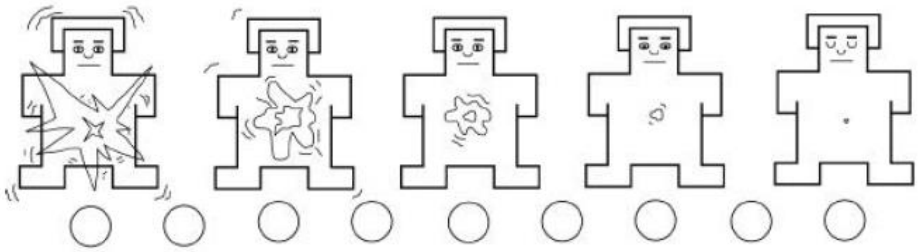
Questionnaire - Part 2

You will be asked to rate your emotions towards to experience in using the system. It will be asked to rate on three separate scales.

Rating Scales

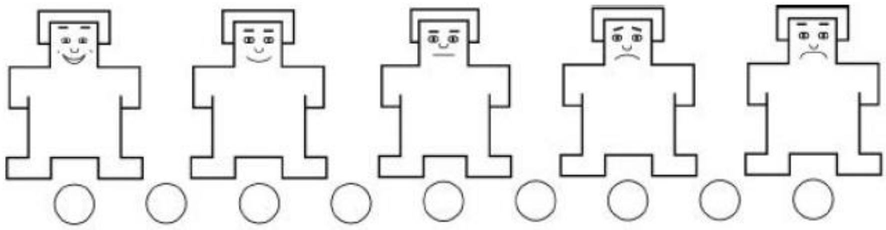
1. **Valence (Pleasant level)**

Unpleasant Unsatisfied Neutral Pleased Pleasant



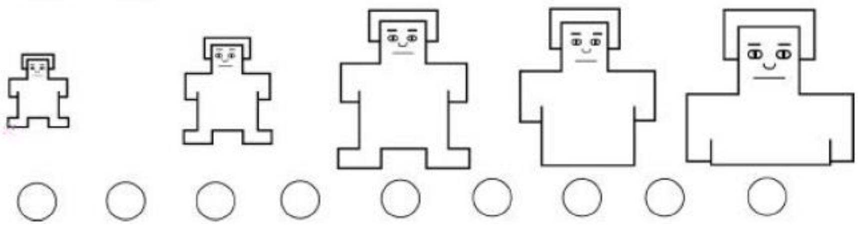
2. **Arousal (Excitement level)**

Excited Wide-awake Neutral Dull Calm



3. **Dominance (Emotion Control level)**

Dependent Powerlessness Neutral Powerful Independent



Questionnaire – Part 3

The evaluation you are about to perform is a technique that has been developed by Nasa to assess the relative importance of six factors in determining how much workload you experienced while preforming a task that you recently completed. These six factors are defined below on this page.
Read through them to make sure you understand what each factor means. If you have any questions, please ask your administrator.

Workload factors	Definition
Mental Demand Level (low/high)	**How much mental add perceptual activity was required** (for example, thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, forgiving or exacting?
Physical Demand Level (low/high)	**How much physical activity was required** (for example, pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?
Temporal Demand Level (low/high)	**How much time pressure did you feel** due to the rate or pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?
Performance Level(good/poor)	**How successful do you think you were in accomplish the goals of the task set by the experimenter** (or yourself)? How satisfied were you with your performance in accomplish these goals?
Effort Level (low/high)	**How hard did you have to work** (mentally and physically) to accomplish your level of performance?
Frustration Level (low/high)	**How insecure, discouraged, irritated, stressed**, and annoyed versus secure, gratified, content, relaxed, and complacent did you feel during the task?

For each pair, choose the factor that was more important to your experience of the workload in the task that you recently performed:		
1	☐ Temporal Demand	☐ Mental Demand
2	☐ Performance	☐ Mental Demand
3	☐ Mental Demand	☐ Effort
4	☐ Temporal Demand	☐ Effort
5	☐ Physical Demand	☐ Performance
6	☐ Performance	☐ Temporal Demand
7	☐ Effort	☐ Physical Demand
8	☐ Mental Demand	☐ Physical Demand
9	☐ Performance	☐ Frustration
10	☐ Effort	☐ Performance
11	☐ Frustration	☐ Effort
12	☐ Frustration	☐ Mental Demand
13	☐ Physical Demand	☐ Temporal Demand
14	☐ Physical Demand	☐ Frustration
15	☐ Temporal Demand	☐ Frustration

You will now be presented with a Series of rating scales for the system.

For each of the six scales, evaluate the task you recently performed by cross on the scale’s location that matches your experience. Each line has two endpoint that describe the scale.

Consider your responses carefully in distinguishing among the different task conditions and consider each individually.

1. Mental Demand (How mentally demanding was the task?/ How much mental and perceptual activity did you spend for this task?)

Very Low Very High

2. Physical Demand (How physically demanding was the task?/ How much physical activity did you spend for this task?)

Very Low Very High

3. Temporal Demand (How hurried or rushed was the pace of the task?/ How much time pressure did you feel in order to complete this task?)

Very Low Very High

4. Performance (How successful were you in accomplishing what you were asked to do?/ How successful do you think you were in accomplishing the goals of the task?)

Good Poor

5. Effort (How hard did you have to work to accomplish your level of performance?)

Very Low Very High

6. Frustration (How insecure, discouraged, irritated, stressed, and annoyed were you during this task?)

Very Low Very High

Appendix J – Statistics Report

This is a report of all variables from E4 and pupil.

1 – How to detect interaction between groups for different variables: ANCOVA

1 – Baseline full factorial – Is there any difference. (Pre-test)
2 – Baseline and Test custom – Homogeneity (Custom test all graphs)
3 – Baseline and Test full factorial– Difference between groups

Heart Rate Variability Analysis

1 - IBI

Variables from IBI – Between Groups

First, we checked that there is no statistically significant difference between baselines, which can let us to do an ANCOVA test. Second, we run the homogeneity test for variables. No interaction was found

Variable	Pre-test	Homogeneity	ANCOVA (Sig)	F	ETA Sq.	Haptic	Sd.	AR	Sd.
MNN	0.858	0.517	0.792	F(1,19)=0,071	0.004	0.7485	0.1610	0.7542	0.2274
SDNN	0.383	0.489	0.341	F(1,17)=0.958	0.053	0.0617	0.0232	0.0948	0.0713
RMSSD	0.340	0.146	0.185	F(1,17)=1.912	0.101	0.0880	0.0320	0.1170	0.0450

Variables from IBI – Between (Gender)

Variable	ANCOVA (Sig)	F	ETA Sq.	Haptic	Sd.	AR	Sd.
MNN (M)	0.366	F(1,7)=0.933	0.118	0.818	0.221	0.691	0.117
MNN (F)	0.332	F(1,9)=1.05	0.105	0.692	0.078	0.8078	0.2911

Variables from IBI – Within Groups

Haptic					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
MNN_Baseline	0.436	0.709	0.110	0.599	0.820
MNN_Test		0.749	0.161	0.587	0.910
SDNN_Baseline	0.297	0.095	0.071	0.024	0.166
SDNN_Test		0.062	0.023	0.039	0.085
RMSSD_Baseline	0.358	0.106	0.043	0.062	0.149
RMSSD_Test		0.088	0.032	0.056	0.120
AR					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
MNN_Baseline	0.166	0.699	0.170	0.528	0.869
MNN_Test		0.754	0.227	0.527	0.982
SDNN_Baseline	0.226	0.065	0.031	0.034	0.096
SDNN_Test		0.095	0.071	0.024	0.166
RMSSD_Baseline	0.205	0.089	0.043	0.046	0.133
RMSSD_Test		0.118	0.045	0.073	0.163

Variables from IBI – Within Groups and Gender

MALE (Haptic)					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
MNN_Baseline	0.340	0.7189	0.0505	0.668	0.769
MNN_Test		0.8190	0.2215	0.597	1.040
SDNN_Baseline	0.396	0.1257	0.0915	0.034	0.217
SDNN_Test		0.0673	0.0312	0.036	0.098
RMSSD_Baseline	0.511	0.1214	0.0377	0.084	0.159
FEMALE (Haptic)					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
MNN_Baseline	0.848	0.701	0.149	0.553	0.851
MNN_Test		0.692	0.078	0.614	0.771
SDNN_Baseline	0.606	0.064	0.030	0.034	0.096
SDNN_Test		0.056	0.014	0.042	0.071
RMSSD_Baseline	0.611	0.090	0.048	0.042	0.139
MALE (AR)					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
MNN_Baseline	0.340	0.719	0.050	0.668	0.769
MNN_Test		0.819	0.222	0.597	1.040
SDNN_Baseline	0.396	0.126	0.092	0.034	0.217
SDNN_Test		0.067	0.031	0.036	0.098
RMSSD_Baseline	0.511	0.121	0.038	0.084	0.159
FEMALE (AR)					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
MNN_Baseline	0.220	0.728	0.169	0.559	0.898
MNN_Test		0.808	0.291	0.517	1.099
SDNN_Baseline	0.394	0.055	0.022	0.034	0.077
SDNN_Test		0.069	0.024	0.044	0.093
RMSSD_Baseline	0.317	0.074	0.023	0.052	0.097

For the IBI analysis we found no correlation between and within groups as expected. This variable could assess some diseases and variability of the heart rate.

2- Heart Rate

Variables from HR – Between Groups

First, we checked that there's no statistically significant difference between baselines, which can let us to do an ANCOVA test. Second, we run the homogeneity test for variables. No interaction was found

Variable	Pre-test	Homogeneity	ANCOVA (Sig)	F	ETA Sq.	Haptic	Sd.	AR	Sd.
HR	0.431	0.342	0.694	F(1,43)=0.157	0.004	86.2	14.64	87.78	6.90
rangeHR	0.051	03057	0.382	F(1,43)=0.779	0.018	17.38	15.37	15.19	6.29

Variables from HR – Between Gender

Variable	ANCOVA (Sig)	F	ETA Sq.	Haptic	Sd.	AR	Sd.
HR (M)*	0.722	F(1,20)=0.130	0.006	85.225	6.357	87.281	20.62

HR (F)*	0.601	F(1,20)=0.283	0.014	87.017	7.188	88.62	6.814
rangeHR(M)	0.144	F(1,18)=2.338	0.115	22.61	20.53	15.93	7.27
rangeHR(F)	0.370	1,20 =0.843	0.040	12.58	6.06	14.52	5.47

Variables from HR – Within Groups

Haptic					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
HR_Baseline	0.927	86.512	8.604	77.909	95.116
HR_Test		86.209	14.650	71.559	100.859
RangeHR_Base	0.111	11.280	6.170	5.109	17.450
RangeHR_Test		17.380	15.372	2.009	32.752
AR					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
HR_Baseline	0.625	89.670	17.016	72.653	106.686
HR_Test		87.785	6.901	80.884	94.686
RangeHR_Base	0.289	17.796	14.273	3.522	32.069
RangeHR_Test		15.196	6.292	8.904	21.487

Variables from HR– Within Groups and Gender

MALE (Haptic)					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
HR_Baseline	0.868	86.151	10.338	75.813	96.490
HR_Test		87.281	20.622	66.659	107.903
RangeHR_Base	0.128	11.270	5.569	5.701	16.839
RangeHR_Test		22.610	20.535	2.075	43.145
FEMALE (Haptic)					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
HR_Baseline	0.427	86.843	7.116	79.727	93.959
HR_Test		85.226	6.357	78.868	91.583
RangeHR_Base	0.666	11.288	6.924	4.364	18.212
RangeHR_Test		12.587	6.069	6.518	18.655
MALE (AR)					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
HR_Baseline	0.843	90.243	23.319	66.924	113.561
HR_Test		88.623	6.815	81.808	95.437
RangeHR_Base	0.618	17.163	11.917	5.246	29.079
RangeHR_Test		15.933	7.274	8.659	23.207
FEMALE (AR)					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
HR_Baseline	0.207	89.145	9.174	79.971	98.319
HR_Test		87.017	7.188	79.829	94.206
RangeHR_Base	0.368	18.376	16.661	1.715	35.037
RangeHR_Test		14.520	5.479	9.041	19.999

Parallel differences for different types of events – Between groups

Group (1-haptic 2 AR)		Sig. (2-tailed)	Mean	Std. Deviation	Std. Error Mean
meanHR	1	0.753	-1.885	18.213	3.798
	2		-0.303	15.606	3.254
rangeHR	1	0.054	-2.600	11.464	2.390
	2		6.101	17.640	3.678
meanHRvarus	1	0.298	-3.857	8.763	3.919
	2		0.883	3.745	1.675
rangeHRvarus	1	0.528	-7.538	15.453	7.727
	2		-0.987	6.462	3.731
meanHRvalgus	1	0.898	-4.994	18.600	5.369
	2		-5.800	6.875	2.174
rangeHRvalgus	1	0.187	-7.540	12.471	3.944
	2		1.115	14.183	5.014
meanHRalignment	1	0.316	-3.511	20.196	4.211
	2		2.424	17.076	3.917
rangeHRalignment	1	**0.033**	-5.272	11.573	2.413
	2		4.874	17.955	4.119
meanHR2E	1	0.848	-2.195	18.543	3.867
	2		-1.180	13.043	3.163
rangeHR2E	1	0.095	-4.640	11.728	2.445
	2		2.939	15.473	3.995
meanHR1A	1	0.708	-2.316	18.698	3.899
	2		-0.459	14.470	3.017
rangeHR1A	1	0.089	-5.399	11.880	2.477
	2		2.137	17.027	3.550

Parallel differences for different types of events – Between groups MALE

Group (1-haptic 2 AR)		Sig. (2-tailed)	Mean	Std. Deviation	Std. Error Mean
meanHR	Haptic	0.793	1.130	21.925	6.611
	AR		-1.620	26.387	7.956
rangeHR	Haptic	0.098	11.340	22.670	6.835
	AR		-1.230	7.919	2.388
meanHRvarus	Haptic	0.567	-0.202	4.027	2.847
	AR		-4.192		
rangeHRvarus	Haptic		-3.530		
	AR		2.280		
meanHRvalgus	Haptic	0.787	-5.330	7.491	3.058
	AR		-7.989	22.406	7.922
rangeHRvalgus	Haptic	0.410	-0.568	14.502	6.485
	AR		-7.390	11.723	4.786
meanHRalignment	Haptic	0.544	4.135	24.719	8.240
	AR		-3.455	29.232	8.814
rangeHRalignment	Haptic	**0.039**	11.956	23.713	7.904
	AR		-5.132	8.787	2.649
meanHR2E	Haptic	0.887	-0.482	18.232	6.446

	AR		-2.074	26.858	8.098
rangeHR2E	Haptic	0.181	6.138	21.421	8.096
	AR		-3.824	8.486	2.559
meanHR1A	Haptic	0.760	0.889	20.133	6.070
	AR		-2.258	27.076	8.164
rangeHR1A	Haptic	0.115	7.109	22.270	6.715
	AR		-4.809	8.841	2.666

Parallel differences for different types of events – Between groups Female

Group (1-haptic 2 AR)		Sig. (2-tailed)	Mean	Std. Deviation	Std. Error Mean
meanHR	Haptic	0.842	-1.617	6.792	1.961
	AR		-2.128	5.503	1.589
rangeHR	Haptic	0.318	1.298	10.125	2.923
	AR		-3.856	14.221	4.105
meanHRvarus	Haptic	0.434	1.606	4.240	2.448
	AR		-3.773	10.116	5.058
rangeHRvarus	Haptic	0.473	0.285	8.591	6.075
	AR		-10.810	17.145	9.898
meanHRvalgus	Haptic	0.129	-6.505	6.869	3.434
	AR		0.996	5.035	2.517
rangeHRvalgus	Haptic	0.376	3.920	16.265	9.390
	AR		-7.765	15.408	7.704
meanHRalignment	Haptic	0.103	0.885	5.874	1.857
	AR		-3.562	6.234	1.800
rangeHRalignment	Haptic	0.435	-1.500	7.042	2.227
	AR		-5.401	14.059	4.058
meanHR2E	Haptic	0.856	-1.800	6.963	2.321
	AR		-2.307	5.647	1.630
rangeHR2E	Haptic	0.341	0.140	8.143	2.879
	AR		-5.388	14.434	4.167
meanHR1A	Haptic	0.796	-1.694	6.841	1.975
	AR		-2.369	5.722	1.652
rangeHR1A	Haptic	0.483	-2.422	9.033	2.608
	AR		-5.940	14.510	4.189

EDA Analysis

Skin conductance can be an indication of psychological or physiological arousal.

Variables from EDA – Between Groups

First, we checked that there is no statistically significant difference between baselines, which can let us to do an ANCOVA test. Second, we run the homogeneity test for variables. No interaction was found

Variable	Pre-test	Homogeneity	ANCOVA (Sig)	F	ETA Sq.	Haptic	Sd.	AR	Sd.
meanEDA	0.619	0.925	0.693	F(1,43)=0.158	0.004	0.5284	0.861	0.458	0.772
1derEDA	0.972	0.475	0.523	F(1,41)=0.414	0.010	0.40*E-4	3.3E-3	1.1E-4	5.1E-3
2derEDA	0.340	0.153	0.185	F(1,35)=2.432	0.065	-2.443E-3	5.3E-3	-3.37E-4	1.2E-3

Variables from EDA – Between Groups and Gender

Variable	ANCOVA (Sig)	F	ETA Sq.	Haptic	Sd.	AR	Sd.
meanEDA(M)	0.492	F(1,19)=0.492	0.025	0.678	1.113	0.4544	0.625
meanEDA(F)	0.433	F(1,21)=0.639	0.030	0.390	0.560	0.462	0.915
1derEDA (M)	0.365	F(1,19)=0.861	0.043	-3.6E-3	6.82E-3	-8.5E-5	4.3E-4
1derEDA (F)	0.524	F(1,19)=0.421	0.022	4.5e-4	3.4E-3	3.31E-4	1.21E-3
2derEDA (M)	0.123	F(1,18)=2.621	0.127	-3.6E-3	6.82E-3	-8.5E-5	4.3E-4
2derEDA (F)	0.863	F(1,14)=0.031	0.002	-1.1E-3	2.98E-3	-6.97E-4	1.9E-3

Variables from EDA – Within Groups

Haptic					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
meanEDABaseline	0.025	0.373	0.671	-0.298	1.045
meanEDATest		0.528	0.862	-0.333	1.390
meanEDABaseline	0.097	0.281	0.179	0.102	0.461
meanEDAC1C6		0.350	0.219	0.131	0.568
meanEDABaseline	0.048	0.533	0.957	-0.425	1.490
meanEDAC3C4		0.682	1.128	-0.447	1.810
meanEDABaseline	0.047	0.411	0.733	-0.322	1.145
meanEDAC2C5		0.567	0.937	-0.369	1.504
meanEDABaseline	0.065	0.433	0.766	-0.332	1.199
meanEDA2E		0.610	0.941	-0.332	1.551
meanEDABaseline	0.022	0.373	0.671	-0.298	1.045
meanEDA1A		0.522	0.843	-0.321	1.365
meanFirstDerivativeEDABaseline	0.310	-0.001	0.006	-0.008	0.005
meanFirstDerivativeEDATest		0.000	0.003	-0.003	0.004
meanFirstDerivativeEDABaseline	0.474	0.000	0.000	0.000	0.000

meanFirstDerivativeEDAC1C6		0.000	0.000	0.000	0.001
meanFirstDerivativeEDABaseline	0.490	-0.003	0.009	-0.012	0.006
meanFirstDerivativeEDAC3C4		0.002	0.014	-0.012	0.016
meanFirstDerivativeEDABaseline	0.743	-0.002	0.007	-0.009	0.005
meanFirstDerivativeEDAC2C5		-0.005	0.030	-0.034	0.025
meanFirstDerivativeEDABaseline	0.110	-0.002	0.007	-0.009	0.005
meanFirstDerivativeEDA2E		0.030	0.070	-0.040	0.101
meanFirstDerivativeEDABaseline	0.172	-0.001	0.006	-0.007	0.005
meanFirstDerivativeEDA1A		0.018	0.058	-0.040	0.075
meanSecondDerivativeEDABaseline	0.481	-0.007	0.030	-0.037	0.022
meanSecondDerivativeEDATest		-0.002	0.005	-0.008	0.003
meanSecondDerivativeEDABaseline	0.482	0.000	0.000	0.000	0.000
meanSecondDerivativeEDAC1C6		0.006	0.012	-0.006	0.017
meanSecondDerivativeEDABaseline	0.666	-0.015	0.043	-0.058	0.028
meanSecondDerivativeEDAC3C4		-0.005	0.038	-0.043	0.033
meanSecondDerivativeEDABaseline	0.519	-0.009	0.033	-0.042	0.024
meanSecondDerivativeEDAC2C5		-0.032	0.134	-0.165	0.102
meanSecondDerivativeEDABaseline	0.328	-0.009	0.034	-0.043	0.024
meanSecondDerivativeEDA2E		0.094	0.376	-0.282	0.470
meanSecondDerivativeEDABaseline	0.591	-0.007	0.028	-0.035	0.022
meanSecondDerivativeEDA1A		0.010	0.116	-0.106	0.125
AR					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
meanEDABaseline	0.068	0.287	0.485	-0.198	0.772
meanEDATest		0.458	0.773	-0.314	1.231
meanEDABaseline	0.280	0.593	1.027	-0.435	1.620
meanEDAC1C6		0.837	1.465	-0.628	2.302
meanEDABaseline	0.004	0.231	0.148	0.083	0.380
meanEDAC3C4		0.283	0.168	0.115	0.451
meanEDABaseline	0.020	0.287	0.485	-0.198	0.772
meanEDAC2C5		0.404	0.657	-0.253	1.061
meanEDABaseline	0.128	0.317	0.528	-0.212	0.845
meanEDA2E		0.549	0.956	-0.407	1.505
meanEDABaseline	0.090	0.287	0.485	-0.198	0.772
meanEDA1A		0.461	0.788	-0.328	1.249
meanFirstDerivativeEDABaseline	0.124	-0.001	0.004	-0.005	0.003
meanFirstDerivativeEDATest		0.001	0.005	-0.004	0.006

meanFirstDerivativeEDABaseline	0.527	-0.004	0.008	-0.012	0.005
meanFirstDerivativeEDAC1C6		0.000	0.005	-0.005	0.005
meanFirstDerivativeEDABaseline	0.101	0.000	0.001	-0.002	0.001
meanFirstDerivativeEDAC3C4		0.009	0.017	-0.008	0.025
meanFirstDerivativeEDABaseline	0.285	-0.001	0.004	-0.005	0.003
meanFirstDerivativeEDAC2C5		0.013	0.062	-0.048	0.075
meanFirstDerivativeEDABaseline	0.054	-0.001	0.004	-0.006	0.003
meanFirstDerivativeEDA2E		0.009	0.018	-0.009	0.028
meanFirstDerivativeEDABaseline	0.222	-0.001	0.004	-0.005	0.003
meanFirstDerivativeEDA1A		0.005	0.021	-0.017	0.026
meanSecondDerivativeEDABaseline	0.252	-0.007	0.022	-0.029	0.015
meanSecondDerivativeEDATest		0.000	0.001	-0.002	0.001
meanSecondDerivativeEDABaseline	0.550	-0.019	0.040	-0.058	0.021
meanSecondDerivativeEDAC1C6		-0.004	0.016	-0.020	0.012
meanSecondDerivativeEDABaseline	0.779	-0.003	0.005	-0.008	0.002
meanSecondDerivativeEDAC3C4		-0.019	0.192	-0.211	0.173
meanSecondDerivativeEDABaseline	0.176	-0.007	0.021	-0.028	0.014
meanSecondDerivativeEDAC2C5		0.032	0.109	-0.077	0.141
meanSecondDerivativeEDABaseline	0.631	-0.007	0.022	-0.029	0.015
meanSecondDerivativeEDA2E		-0.024	0.143	-0.167	0.119
meanSecondDerivativeEDABaseline	0.584	-0.006	0.020	-0.026	0.013
meanSecondDerivativeEDA1A		-0.013	0.046	-0.059	0.034

Variables from EDA– Within Groups and Gender

MALE (Haptic)					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
meanEDABaseline	0.023	0.523	0.949	-0.426	1.473
meanEDATest		0.678	1.114	-0.435	1.792
meanEDABaseline	0.000	0.426		0.426	0.426
meanEDAC1C6		0.522		0.522	0.522
meanEDABaseline	0.150	0.704	1.244	-0.541	1.948
meanEDAC3C4		0.869	1.459	-0.590	2.329
meanEDABaseline	0.038	0.612	1.039	-0.427	1.650
meanEDAC2C5		0.787	1.227	-0.440	2.014
meanEDABaseline	0.056	0.617	1.159	-0.542	1.776
meanEDA2E		0.766	1.283	-0.517	2.048
meanEDABaseline	0.020	0.523	0.949	-0.426	1.473
meanEDA1A		0.676	1.095	-0.419	1.771

meanFirstDerivativeEDABaseline	0.433	-0.002	0.009	-0.011	0.006
meanFirstDerivativeEDATest		0.000	0.003	-0.003	0.004
meanFirstDerivativeEDABaseline	0.000			0.000	0.000
meanFirstDerivativeEDAC1C6				0.000	0.000
meanFirstDerivativeEDABaseline	0.365	-0.005	0.011	-0.016	0.006
meanFirstDerivativeEDAC3C4		0.006	0.017	-0.010	0.023
meanFirstDerivativeEDABaseline	0.379	-0.003	0.010	-0.013	0.007
meanFirstDerivativeEDAC2C5		0.003	0.010	-0.007	0.013
meanFirstDerivativeEDABaseline	0.189	-0.004	0.010	-0.015	0.006
meanFirstDerivativeEDA2E		0.055	0.097	-0.042	0.151
meanFirstDerivativeEDABaseline	0.255	-0.002	0.009	-0.011	0.006
meanFirstDerivativeEDA1A		0.029	0.080	-0.050	0.109
meanSecondDerivativeEDABaseline	0.477	-0.013	0.041	-0.054	0.028
meanSecondDerivativeEDATest		-0.004	0.007	-0.010	0.003
meanSecondDerivativeEDABaseline	0.000	0.000		0.000	0.000
meanSecondDerivativeEDAC1C6		0.000		0.000	0.000
meanSecondDerivativeEDABaseline	0.712	-0.024	0.055	-0.079	0.031
meanSecondDerivativeEDAC3C4		-0.009	0.050	-0.059	0.041
meanSecondDerivativeEDABaseline	0.429	-0.016	0.045	-0.061	0.029
meanSecondDerivativeEDAC2C5		0.001	0.020	-0.019	0.021
meanSecondDerivativeEDABaseline	0.361	-0.020	0.051	-0.072	0.031
meanSecondDerivativeEDA2E		0.212	0.570	-0.358	0.781
meanSecondDerivativeEDABaseline	0.548	-0.013	0.041	-0.054	0.028
meanSecondDerivativeEDA1A		0.026	0.170	-0.144	0.196
FEMALE (Haptic)					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
meanEDABaseline	0.204	0.236	0.196	0.040	0.432
meanEDATest		0.391	0.561	-0.170	0.952
meanEDABaseline	0.336	0.209	0.182	0.027	0.391
meanEDAC1C6		0.263	0.227	0.037	0.490
meanEDABaseline	0.256	0.276	0.153	0.123	0.428
meanEDAC3C4		0.401	0.309	0.092	0.710
meanEDABaseline	0.305	0.231	0.202	0.029	0.433
meanEDAC2C5		0.370	0.570	-0.201	0.940
meanEDABaseline	0.235	0.291	0.199	0.092	0.489
meanEDA2E		0.488	0.624	-0.136	1.113
meanEDABaseline	0.204	0.236	0.196	0.040	0.432

meanEDA1A		0.381	0.534	-0.154	0.915
meanFirstDerivativeEDABaseline	0.486	-0.001	0.001	-0.002	0.001
meanFirstDerivativeEDATest		0.000	0.003	-0.003	0.004
meanFirstDerivativeEDABaseline	0.474	0.000	0.000	0.000	0.000
meanFirstDerivativeEDAC1C6		0.000	0.000	0.000	0.001
meanFirstDerivativeEDABaseline	0.207	0.000	0.001	-0.001	0.001
meanFirstDerivativeEDAC3C4		-0.004	0.006	-0.010	0.001
meanFirstDerivativeEDABaseline	0.452	-0.001	0.001	-0.002	0.000
meanFirstDerivativeEDAC2C5		-0.011	0.040	-0.051	0.029
meanFirstDerivativeEDABaseline	0.381	-0.001	0.001	-0.002	0.001
meanFirstDerivativeEDA2E		0.011	0.037	-0.026	0.047
meanFirstDerivativeEDABaseline	0.320	0.000	0.001	-0.002	0.001
meanFirstDerivativeEDA1A		0.006	0.019	-0.013	0.025
meanSecondDerivativeEDABaseline	0.805	-0.001	0.002	-0.003	0.001
meanSecondDerivativeEDATest		-0.001	0.003	-0.004	0.002
meanSecondDerivativeEDABaseline	0.558	0.000	0.000	0.000	0.000
meanSecondDerivativeEDAC1C6		0.009	0.015	-0.006	0.023
meanSecondDerivativeEDABaseline	0.231	-0.002	0.003	-0.005	0.002
meanSecondDerivativeEDAC3C4		0.001	0.001	0.000	0.001
meanSecondDerivativeEDABaseline	0.359	-0.001	0.002	-0.004	0.001
meanSecondDerivativeEDAC2C5		-0.068	0.194	-0.262	0.125
meanSecondDerivativeEDABaseline	0.021	-0.001	0.002	-0.003	0.001
meanSecondDerivativeEDA2E		0.003	0.004	-0.001	0.007
meanSecondDerivativeEDABaseline	0.150	-0.001	0.002	-0.003	0.001
meanSecondDerivativeEDA1A		-0.006	0.011	-0.016	0.005
MALE (AR)					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
meanEDABaseline	0.217	0.2277	0.1406	0.2277	0.1406
meanEDATest		0.4544	0.6255	0.4544	0.6255
meanEDABaseline	0.000	0.2446		0.2446	
meanEDAC1C6		0.3421		0.3421	
meanEDABaseline	0.019	0.2459	0.1465	0.2459	0.1465
meanEDAC3C4		0.3072	0.1658	0.3072	0.1658
meanEDABaseline	0.111	0.2277	0.1406	0.2277	0.1406
meanEDAC2C5		0.3566	0.3233	0.3566	0.3233
meanEDABaseline	0.261	0.2554	0.1400	0.2554	0.1400
meanEDA2E		0.6089	0.9178	0.6089	0.9178
meanEDABaseline	0.245	0.2277	0.1406	0.2277	0.1406
meanEDA1A		0.4684	0.6988	0.4684	0.6988
meanFirstDerivativeEDABaseline	0.402	0.0000	0.0007	0.0000	0.0007

meanFirstDerivativeEDATest		0.0020	0.0075	0.0020	0.0075
meanFirstDerivativeEDABaseline	0.000	0.0005		0.0005	
meanFirstDerivativeEDAC1C6		0.0002		0.0002	
meanFirstDerivativeEDABaseline	0.280	0.0001	0.0008	0.0001	0.0008
meanFirstDerivativeEDAC3C4		0.0069	0.0166	0.0069	0.0166
meanFirstDerivativeEDABaseline	0.338	0.0000	0.0007	0.0000	0.0007
meanFirstDerivativeEDAC2C5		0.0285	0.0891	0.0285	0.0891
meanFirstDerivativeEDABaseline	0.216	0.0000	0.0007	0.0000	0.0007
meanFirstDerivativeEDA2E		0.0077	0.0171	0.0077	0.0171
meanFirstDerivativeEDABaseline	0.392	0.0000	0.0007	0.0000	0.0007
meanFirstDerivativeEDA1A		0.0084	0.0312	0.0084	0.0312
meanSecondDerivativeEDABaseline	0.568	-0.0006	0.0023	-0.0006	0.0023
meanSecondDerivativeEDATest		-0.0001	0.0004	-0.0001	0.0004
meanSecondDerivativeEDABaseline	0.000	-0.0001		-0.0001	
meanSecondDerivativeEDAC1C6		-0.0006		-0.0006	
meanSecondDerivativeEDABaseline	0.146	-0.0010	0.0027	-0.0010	0.0027
meanSecondDerivativeEDAC3C4		0.0477	0.0778	0.0477	0.0778
meanSecondDerivativeEDABaseline	0.344	-0.0006	0.0023	-0.0006	0.0023
meanSecondDerivativeEDAC2C5		0.0445	0.1428	0.0445	0.1428
meanSecondDerivativeEDABaseline	0.525	-0.0009	0.0025	-0.0009	0.0025
meanSecondDerivativeEDA2E		0.0094	0.0434	0.0094	0.0434
meanSecondDerivativeEDABaseline	0.376	-0.0006	0.0023	-0.0006	0.0023
meanSecondDerivativeEDA1A		-0.0202	0.0664	-0.0202	0.0664
FEMALE (AR)					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
meanEDABaseline	0.130	0.341	0.667	0.341	0.667
meanEDATest		0.462	0.916	0.462	0.916
meanEDABaseline	0.340	0.680	1.165	0.680	1.165
meanEDAC1C6		0.961	1.661	0.961	1.661
meanEDABaseline	0.043	0.203	0.170	0.203	0.170
meanEDAC3C4		0.234	0.187	0.234	0.187
meanEDABaseline	0.115	0.341	0.667	0.341	0.667
meanEDAC2C5		0.448	0.874	0.448	0.874
meanEDABaseline	0.233	0.372	0.731	0.372	0.731
meanEDA2E		0.495	1.035	0.495	1.035
meanEDABaseline	0.124	0.341	0.667	0.341	0.667
meanEDA1A		0.454	0.894	0.454	0.894
meanFirstDerivativeEDABaseline	0.196	-0.002	0.005	-0.002	0.005
meanFirstDerivativeEDATest		0.000	0.001	0.000	0.001
meanFirstDerivativeEDABaseline	0.538	-0.005	0.009	-0.005	0.009
meanFirstDerivativeEDAC1C6		0.000	0.006	0.000	0.006
meanFirstDerivativeEDABaseline	0.293	-0.001	0.002	-0.001	0.002
meanFirstDerivativeEDAC3C4		0.012	0.019	0.012	0.019
meanFirstDerivativeEDABaseline	0.151	-0.002	0.005	-0.002	0.005
meanFirstDerivativeEDAC2C5		0.000	0.001	0.000	0.001
meanFirstDerivativeEDABaseline	0.162	-0.003	0.006	-0.003	0.006

meanFirstDerivativeEDA2E		0.011	0.021	0.011	0.021
meanFirstDerivativeEDABaseline	0.158	-0.002	0.005	-0.002	0.005
meanFirstDerivativeEDA1A		0.001	0.003	0.001	0.003
meanSecondDerivativeEDABaseline	0.293	-0.015	0.033	-0.015	0.033
meanSecondDerivativeEDATest		-0.001	0.002	-0.001	0.002
meanSecondDerivativeEDABaseline	0.565	-0.023	0.045	-0.023	0.045
meanSecondDerivativeEDAC1C6		-0.005	0.018	-0.005	0.018
meanSecondDerivativeEDABaseline	0.422	-0.006	0.007	-0.006	0.007
meanSecondDerivativeEDAC3C4		-0.136	0.287	-0.136	0.287
meanSecondDerivativeEDABaseline	0.306	-0.014	0.031	-0.014	0.031
meanSecondDerivativeEDAC2C5		0.016	0.046	0.016	0.046
meanSecondDerivativeEDABaseline	0.544	-0.013	0.029	-0.013	0.029
meanSecondDerivativeEDA2E		-0.054	0.193	-0.054	0.193
meanSecondDerivativeEDABaseline	0.579	-0.012	0.027	-0.012	0.027
meanSecondDerivativeEDA1A		-0.006	0.015	-0.006	0.015

Parallel differences for different types of events – Between groups

Group		Sig(2 ta)	Mean	Std. Deviation	Std. Error Mean
meanEDAVarus	Haptic	0.5258	0.0683	0.0397	0.0229
	AR	0.4208	0.2444	0.4378	0.1958
meanFirstDerivativeEDAVarus	Haptic	0.7345	0.0005	0.0007	0.0005
	AR	0.5815	0.0038	0.0123	0.0055
meanSecondDerivativeEDAVarus	Haptic	0.7782	0.0057	0.0115	0.0066
	AR	0.7196	0.0146	0.0500	0.0223
mean1Varus	Haptic				
	AR		0.0220	0.0428	0.0214
mean2Varus	Haptic	0.6621	0.0003		
	AR		0.0118	0.0213	0.0106
mean3Varus	Haptic	0.9169	0.0053	0.0045	0.0032
	AR	0.8871	0.0064	0.0123	0.0061
mean4Varus	Haptic	0.7157	0.0012		
	AR		0.0088	0.0170	0.0085
meanEDAValgus	Haptic	0.1267	0.1494	0.2067	0.0654
	AR	0.1748	0.0515	0.0490	0.0141
meanFirstDerivativeEDAValgus	Haptic	0.6413	0.0050	0.0218	0.0069
	AR	0.6494	0.0089	0.0172	0.0050
meanSecondDerivativeEDAValgus	Haptic	0.6827	0.0099	0.0703	0.0222
	AR	0.6735	-0.0163	0.1879	0.0567
mean1Valgus	Haptic	0.2333	0.0331	0.0527	0.0186
	AR	0.1489	0.0028	0.0032	0.0014
mean2Valgus	Haptic	0.5338	0.0077	0.0107	0.0038
	AR	0.5170	0.0043	0.0081	0.0033
mean3Valgus	Haptic	0.3086	0.0167	0.0369	0.0130
	AR	0.2923	0.0019	0.0027	0.0010
mean4Valgus	Haptic	0.3408	0.0210	0.0486	0.0172
	AR	0.2852	0.0010	0.0026	0.0011

meanEDAAlignment	Haptic	0.6463	0.1559	0.3183	0.0730
	AR	0.6576	0.1171	0.2245	0.0468
meanFirstDerivativeEDAAlignment	Haptic	0.3010	-0.0026	0.0324	0.0079
	AR	0.2731	0.0147	0.0614	0.0134
meanSecondDerivativeEDAAlignment	Haptic	0.1709	-0.0228	0.1423	0.0345
	AR	0.1742	0.0383	0.1150	0.0271
mean1Alignment	Haptic	0.1654	0.0112	0.0297	0.0074
	AR	0.2235	0.0017	0.0039	0.0009
mean2Alignment	Haptic	0.6205	0.0106	0.0271	0.0066
	AR	0.5759	0.0213	0.0845	0.0176
mean3Alignment	Haptic	0.1970	0.0068	0.0161	0.0039
	AR	0.2380	0.0017	0.0066	0.0014
mean4Alignment	Haptic	0.7191	0.0098	0.0211	0.0050
	AR	0.6928	0.0151	0.0592	0.0123
meanEDA2E	Haptic	0.7549	0.1763	0.3544	0.0886
	AR	0.7440	0.2325	0.6350	0.1457
meanFirstDerivativeEDA2E	Haptic	0.2519	0.0323	0.0762	0.0190
	AR	0.2832	0.0105	0.0215	0.0051
meanSecondDerivativeEDA2E	Haptic	0.2618	0.1036	0.4097	0.1024
	AR	0.2789	-0.0172	0.1444	0.0350
meant12E	Haptic	0.8750	0.0209	0.0434	0.0120
	AR	0.8765	0.0241	0.0562	0.0162
meant22E	Haptic	0.6060	0.0182	0.0488	0.0131
	AR	0.6082	0.0108	0.0205	0.0055
meant32E	Haptic	0.5992	0.0112	0.0291	0.0081
	AR	0.5931	0.0197	0.0501	0.0134
meant42E	Haptic	0.3018	0.0230	0.0513	0.0137
	AR	0.3211	0.0081	0.0182	0.0047
meanEDA1A	Haptic	0.8258	0.1484	0.2898	0.0604
	AR	0.8260	0.1739	0.4706	0.0981
meanFirstDerivativeEDA1A	Haptic	0.3467	0.0190	0.0631	0.0135
	AR	0.3586	0.0058	0.0219	0.0046
meanSecondDerivativeEDA1A	Haptic	0.4981	0.0162	0.1428	0.0298
	AR	0.4847	-0.0064	0.0523	0.0114
meant11A	Haptic	0.2992	0.0266	0.0538	0.0120
	AR	0.3128	0.0125	0.0313	0.0067
meant21A	Haptic	0.2360	0.0217	0.0517	0.0110
	AR	0.2487	0.0080	0.0175	0.0036
meant31A	Haptic	0.3967	0.0109	0.0226	0.0047
	AR	0.3929	0.0061	0.0143	0.0030
meant41A	Haptic	0.6960	0.0096	0.0205	0.0044
	AR	0.6950	0.0069	0.0240	0.0050
Parallel differences for different types of events – Between groups and gender Male					
Group		Sig (2-tailed)	Mean	Std. Deviation	Std. Error Mean
meanEDAVarus	Haptic	0	0.096		
	AR	0	0.097		

meanFirstDerivativeEDAVarus	Haptic	0			
	AR	0	0.000		
meanSecondDerivativeEDAVarus	Haptic	0	0.000		
	AR	0	-0.001		
mean1Varus	Haptic	0			
	AR	0	0.001		
mean2Varus	Haptic	0			
	AR	0	0.001		
mean3Varus	Haptic	0			
	AR	0	0.001		
mean4Varus	Haptic	0			
	AR	0	0.000		
meanEDAValgus	Haptic	0.251	0.166	0.239	0.097
	AR	0.339	0.061	0.057	0.020
meanFirstDerivativeEDAValgus	Haptic	0.722	0.011	0.027	0.011
	AR	0.744	0.007	0.016	0.006
meanSecondDerivativeEDAValgus	Haptic	0.491	0.015	0.094	0.038
	AR	0.500	0.049	0.077	0.029
mean1Valgus	Haptic	0.286	0.039	0.064	0.029
	AR	0.260	0.002	0.003	0.001
mean2Valgus	Haptic	0.557	0.009	0.012	0.006
	AR	0.558	0.005	0.009	0.004
mean3Valgus	Haptic	0.323	0.024	0.047	0.021
	AR	0.351	0.002	0.003	0.001
mean4Valgus	Haptic	0.305	0.031	0.061	0.027
	AR	0.334	0.001	0.003	0.001
meanEDAAlignment	Haptic	0.660	0.175	0.212	0.071
	AR	0.655	0.129	0.244	0.074
meanFirstDerivativeEDAAlignment	Haptic	0.502	0.006	0.019	0.007
	AR	0.462	0.029	0.089	0.028
meanSecondDerivativeEDAAlignment	Haptic	0.591	0.017	0.061	0.020
	AR	0.580	0.045	0.143	0.045
mean1Alignment	Haptic	0.334	0.006	0.009	0.003
	AR	0.351	0.003	0.006	0.002
mean2Alignment	Haptic	0.654	0.017	0.038	0.013
	AR	0.610	0.038	0.121	0.037
mean3Alignment	Haptic	0.195	0.010	0.021	0.007
	AR	0.243	0.000	0.001	0.000
mean4Alignment	Haptic	0.591	0.009	0.020	0.007
	AR	0.537	0.026	0.084	0.025
meanEDA2E	Haptic	0.555	0.149	0.166	0.063
	AR	0.512	0.354	0.878	0.293
meanFirstDerivativeEDA2E	Haptic	0.169	0.059	0.106	0.040
	AR	0.248	0.008	0.017	0.006
meanSecondDerivativeEDA2E	Haptic	0.329	0.232	0.621	0.235
	AR	0.381	0.010	0.043	0.015

meant12E	Haptic	0.987	0.033	0.059	0.024
	AR	0.987	0.032	0.075	0.031
meant22E	Haptic	0.560	0.008	0.011	0.005
	AR	0.542	0.015	0.025	0.009
meant32E	Haptic	0.608	0.020	0.043	0.017
	AR	0.645	0.011	0.022	0.008
meant42E	Haptic	0.549	0.026	0.056	0.023
	AR	0.579	0.012	0.024	0.009
meanEDA1A	Haptic	0.668	0.153	0.183	0.055
	AR	0.671	0.241	0.646	0.195
meanFirstDerivativeEDA1A	Haptic	0.414	0.032	0.087	0.026
	AR	0.420	0.008	0.031	0.009
meanSecondDerivativeEDA1A	Haptic	0.405	0.039	0.209	0.063
	AR	0.393	-0.020	0.067	0.021
meant11A	Haptic	0.289	0.051	0.073	0.024
	AR	0.320	0.022	0.043	0.013
meant21A	Haptic	0.318	0.036	0.070	0.021
	AR	0.326	0.013	0.024	0.007
meant31A	Haptic	0.385	0.018	0.030	0.009
	AR	0.387	0.008	0.017	0.005
meant41A	Haptic	0.754	0.016	0.027	0.008
	AR	0.754	0.012	0.034	0.010
FEMALE					
Group		Sig (2-tailed)	Mean	Std. Deviation	Std. Error Mean
meanEDAVarus	Haptic	0.576	0.055	0.045	0.032
	AR	0.430	0.281	0.497	0.248
meanFirstDerivativeEDAVarus	Haptic	0.700	0.001	0.001	0.000
	AR	0.579	0.005	0.014	0.007
meanSecondDerivativeEDAVarus	Haptic	0.832	0.009	0.015	0.010
	AR	0.765	0.018	0.057	0.028
mean1Varus	Haptic				
	AR		0.029	0.049	0.029
mean2Varus	Haptic	0.652	0.000		
	AR		0.015	0.025	0.014
mean3Varus	Haptic	0.808	0.005	0.004	0.003
	AR	0.769	0.008	0.014	0.008
mean4Varus	Haptic	0.692	0.001		
	AR		0.012	0.020	0.011
meanEDAValgus	Haptic	0.340	0.125	0.179	0.089
	AR	0.375	0.032	0.019	0.009
meanFirstDerivativeEDAValgus	Haptic	0.156	-0.004	0.005	0.003
	AR	0.194	0.013	0.021	0.010
meanSecondDerivativeEDAValgus	Haptic	0.381	0.002	0.003	0.002
	AR	0.415	-0.130	0.281	0.140
mean1Valgus	Haptic	0.735	0.023	0.036	0.021
	AR		0.007		
mean2Valgus	Haptic	0.774	0.006	0.009	0.005
	AR		0.002		

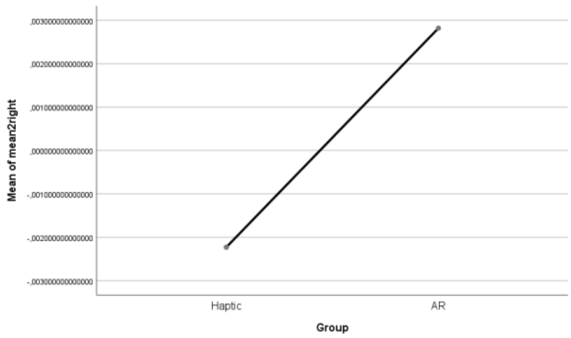
mean3Valgus	Haptic	0.599	0.004	0.007	0.004
	AR	0.528	0.001	0.000	0.000
mean4Valgus	Haptic	0.635	0.004	0.006	0.004
	AR		0.000		
meanEDAAlignment	Haptic	0.813	0.139	0.403	0.127
	AR	0.823	0.106	0.215	0.062
meanFirstDerivativeEDAAlignment	Haptic	0.309	-0.011	0.040	0.013
	AR	0.372	0.002	0.005	0.001
meanSecondDerivativeEDAAlignment	Haptic	0.209	-0.067	0.194	0.069
	AR	0.220	0.030	0.077	0.027
mean1Alignment	Haptic	0.240	0.016	0.042	0.015
	AR	0.339	0.001	0.001	0.000
mean2Alignment	Haptic	0.837	0.005	0.012	0.004
	AR	0.825	0.006	0.019	0.005
mean3Alignment	Haptic	0.757	0.004	0.011	0.004
	AR	0.765	0.003	0.009	0.002
mean4Alignment	Haptic	0.550	0.010	0.023	0.007
	AR	0.561	0.005	0.017	0.005
meanEDA2E	Haptic	0.683	0.198	0.462	0.154
	AR	0.690	0.124	0.306	0.097
meanFirstDerivativeEDA2E	Haptic	0.907	0.012	0.037	0.012
	AR	0.907	0.013	0.026	0.009
meanSecondDerivativeEDA2E	Haptic	0.502	0.004	0.004	0.001
	AR	0.511	-0.041	0.197	0.066
meant12E	Haptic	0.748	0.011	0.024	0.009
	AR	0.757	0.016	0.034	0.014
meant22E	Haptic	0.468	0.026	0.065	0.023
	AR	0.449	0.007	0.016	0.006
meant32E	Haptic	0.345	0.003	0.005	0.002
	AR	0.406	0.031	0.075	0.030
meant42E	Haptic	0.414	0.021	0.051	0.018
	AR	0.425	0.005	0.012	0.004
meanEDA1A	Haptic	0.804	0.145	0.371	0.107
	AR	0.804	0.113	0.235	0.068
meanFirstDerivativeEDA1A	Haptic	0.629	0.006	0.020	0.006
	AR	0.644	0.003	0.008	0.002
meanSecondDerivativeEDA1A	Haptic	0.308	-0.005	0.011	0.003
	AR	0.334	0.006	0.033	0.010
meant11A	Haptic	0.416	0.007	0.015	0.005
	AR	0.422	0.003	0.005	0.001
meant21A	Haptic	0.437	0.007	0.017	0.005
	AR	0.459	0.003	0.006	0.002
meant31A	Haptic	0.825	0.005	0.012	0.003
	AR	0.824	0.004	0.011	0.003
meant41A	Haptic	0.818	0.003	0.007	0.002
	AR	0.819	0.002	0.006	0.002

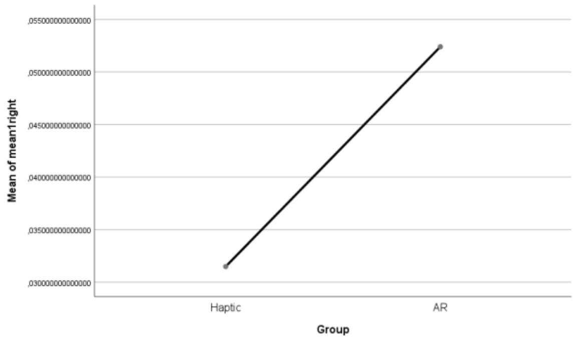
Pupil Analysis

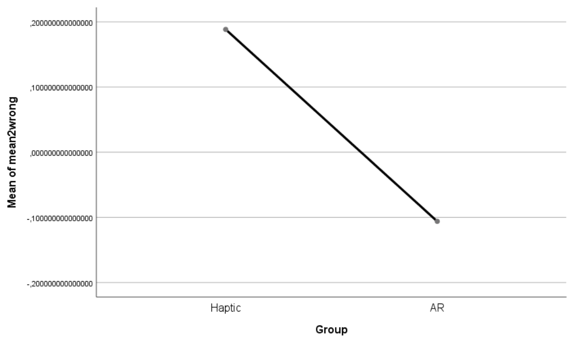
Variables from pupil – Between Groups

First, we checked that there is no statistically significant difference between baselines, which can let us to do ANOVA test. Second, we run the homogeneity test for variables. There are three events for pupil: 2 Error (both legs misaligned), 1 Error (1 Leg misaligned), 2 Right (both legs aligned). Pupil increased diameter for AR feedback for 2 right and 1 Error but not significant. There was a significant increase in pupil diameter for haptic feedback when both legs were misaligned (stress state), which is an unexpected result. The plot confirms this

Variable	Pre-test	Homogeneity	ANOVA (Sig)	F	Haptic	Sd.	AR	Sd.
Mean2Right	1	0.409	0.961	F(1,39)=0,002	-0.002	0.288	0.003	0.370
Mean1Right	0.383	0.861	0.736	F(1,41)=0.115	0.031	0.207	0.052	0.198
Mean2Wrong	0.340	0.345	**0.037**	F(1,36)=4.681	0.188	0.501	-0.106	0.329







Variables from pupil – Between Groups and gender

No Difference was found between genders.

Variables from pupil by event– Between groups

	1H 2 AR		df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% CI	
	Mean	Std. Deviation					Lower	Upper
meanbaselineP	0.000	0.000	39.000	0.996	0.000	0.000	0.000	0.000

	0.000	0.000	38.778	0.996	0.000	0.000	0.000	0.000
meanTestP	0.000	0.000	41.000	0.949	0.000	0.000	0.000	0.000
	0.000	0.000	40.813	0.949	0.000	0.000	0.000	0.000
mean2right	-0.006	0.295	37.000	0.964	-0.004	0.093	-0.193	0.185
	-0.002	0.288	36.779	0.964	-0.004	0.093	-0.194	0.185
mean1right	0.040	0.208	41.000	0.892	0.009	0.063	-0.119	0.136
	0.031	0.207	40.887	0.892	0.009	0.063	-0.119	0.136
mean2wrong	0.177	0.514	33.000	0.950	-0.011	0.172	-0.360	0.338
	0.188	0.501	32.764	0.950	-0.011	0.172	-0.360	0.339
mean2E1R	-0.095	0.308	29.000	**0.049**	-0.247	0.120	-0.492	-0.001
	0.152	0.360	27.642	0.050	-0.247	0.121	-0.494	0.000
mean1R2E	0.144	0.381	31.000	0.091	0.243	0.139	-0.041	0.526
	-0.099	0.410	30.595	0.089	0.243	0.138	-0.039	0.524
mean2R1E	0.064	0.446	38.000	0.288	0.153	0.142	-0.134	0.441
	-0.089	0.451	37.683	0.287	0.153	0.142	-0.134	0.441
mean1E2R	-0.123	0.380	38.000	0.179	-0.146	0.107	-0.362	0.070
	0.023	0.293	33.762	0.185	-0.146	0.108	-0.366	0.074

Variables from pupil by event– Between groups and gender - no difference and effect found

Variables from pupil –Within Groups

Variables from HR– Within Groups and Gender

MALE (Haptic)					
Variable	Sig(2-tailed)	Mean	Std. Dev	Lower	Upper
Variable	Sig. (2-tailed)	mean	Std. Dev	Lower	Upper
meanbaselineP		z-score	0.000		
meanTestP		z-score	0.000		
mean2right	0.665	0.056	0.243	-0.18721	0.299504
mean2wrong		0.158	0.596	-0.43853	0.754461
mean2right	0.616	0.049	0.230	-0.18105	0.279817
mean1right		0.001	0.114	-0.11309	0.115678
mean1right	0.288	-0.005	0.112	-0.11732	0.107633
mean2wrong		0.184	0.568	-0.38445	0.752177
mean2E1R	0.753	0.105	0.509	-0.40406	0.61342
meanb2E1R		0.134	0.647	-0.51356	0.781389
mean1R2E	0.920	0.122	0.623	-0.5007	0.744845
meanb1R2E		0.109	0.311	-0.20238	0.419904
mean2R1E	0.952	0.054	0.265	-0.21087	0.318857
meanb2R1E		0.049	0.230	-0.18099	0.279783
mean1E2R	0.877	0.044	0.235	-0.19077	0.278728
meanb1E2R		0.055	0.203	-0.14829	0.258414
FEMALE(Haptic)					
meanbaselineP		z-score	0.000		
meanTestP		z-score	0.000		
mean2right	0.706	0.0271	0.346	-0.31897	0.373098
mean2wrong		0.1211	0.421	-0.29953	0.541794
mean2right	0.459	-0.0538	0.341	-0.39435	0.286665
mean1right		0.0875	0.277	-0.18916	0.364063
mean1right	0.126	-0.0699	0.139	-0.20909	0.069266

mean2wrong		0.1940	0.441	-0.24664	0.634719
mean2E1R	0.205	0.1189	0.493	-0.37416	0.611947
meanb2E1R		0.2914	0.489	-0.19794	0.780676
mean1R2E	**0.016**	0.2832	0.512	-0.22829	0.79478
meanb1R2E		-0.0616	0.425	-0.4862	0.363096
mean2R1E	0.489	0.1077	0.342	-0.23378	0.449264
meanb2R1E		-0.0245	0.367	-0.39137	0.342369
mean1E2R	0.110	-0.0720	0.333	-0.4051	0.261133
meanb1E2R		0.1866	0.282	-0.09539	0.468607
MALE(AR)					
Variable	Sig. (2-tailed)	mean	Std. Dev	Lower	Upper
meanbaselineP		z-score	0.000		
meanTestP		z-score	0.000		
mean2right	0.276	0.045	0.306	-0.26125	0.350952
mean2wrong		-0.143	0.288	-0.43043	0.145283
mean2right	0.513	0.027	0.294	-0.26644	0.321221
mean1right		0.078	0.202	-0.12317	0.279946
mean1right	0.117	0.061	0.206	-0.14467	0.266933
mean2wrong		-0.143	0.288	-0.43043	0.145283
mean2E1R	0.363	0.048	0.280	-0.23121	0.328118
meanb2E1R		-0.048	0.228	-0.27554	0.180195
mean1R2E	0.154	-0.524	1.161	-1.68423	0.636829
meanb1R2E		-0.300	1.235	-1.53478	0.935485
mean2R1E	0.761	0.000	0.349	-0.34899	0.348533
meanb2R1E		0.029	0.292	-0.26225	0.321037
mean1E2R	0.442	0.017	0.292	-0.27511	0.308376
meanb1E2R		-0.048	0.345	-0.39218	0.297037
FEMALE(AR)					
Variable	Sig. (2-tailed)	mean	Std. Dev	Lower	Upper
meanbaselineP		z-score	0.000		
meanTestP		z-score	0.000		
mean2right	0.803	-0.020	0.442	-0.46112	0.422072
mean2wrong		-0.076	0.370	-0.44609	0.293499
mean2right	0.779	-0.020	0.442	-0.46112	0.422072
mean1right		0.029	0.201	-0.1719	0.229469
mean1right	0.341	0.029	0.201	-0.1719	0.229469
mean2wrong		-0.076	0.370	-0.44609	0.293499
mean2E1R	0.241	0.075	0.391	-0.31629	0.465617
meanb2E1R		-0.126	0.631	-0.75661	0.505172
mean1R2E	0.834	-0.151	0.506	-0.6572	0.355287
meanb1R2E		-0.178	0.606	-0.78369	0.42767
mean2R1E	0.420	-0.119	0.409	-0.52719	0.290035
meanb2R1E		0.025	0.449	-0.42371	0.473649
mean1E2R	0.893	-0.090	0.360	-0.44989	0.270335
meanb1E2R		-0.076	0.487	-0.56323	0.411296

Frequency Domain Analysis – Electrodermal Activity analysis (EDA). Between Groups

Indicator	Description
F0SC	The spectral power in bandwidths 0.05 to 0.1
F1SC	The spectral power in bandwidths 0.1 to 0.2
F2SC	The spectral power in bandwidths 0.2 to 0.3
F3SC	The spectral power in bandwidths 0.3 to 0.4

Within subject analysis

Haptic

	Paired Differences					t	df	Sig. (2-t)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
meanbl1 - meant1	-0.005	0.011	0.002	-0.010	0.000	-2.282	22	0.033
meanbl1 - meant134	-0.033	0.053	0.019	-0.077	0.011	-1.776	7	0.119
meanbl1 - meant125	-0.011	0.030	0.007	-0.027	0.005	-1.511	15	0.152
meanbl1 - meant12E	-0.021	0.043	0.012	-0.047	0.005	-1.737	12	0.108
meanbl1 - meant11A	-0.027	0.054	0.012	-0.052	-0.001	-2.208	19	0.040
meanbl2 - meant2	-0.004	0.009	0.002	-0.008	0.000	-2.203	22	0.038
meanbl2 - meant234	-0.008	0.011	0.004	-0.017	0.001	-2.039	7	0.081
meanbl2 - meant225	-0.011	0.027	0.007	-0.025	0.003	-1.618	16	0.125
meanbl2 - meant22E	-0.018	0.049	0.013	-0.046	0.010	-1.391	13	0.188
meanbl2 - meant21A	-0.022	0.052	0.011	-0.045	0.001	-1.965	21	0.063
meanbl3 - meant3	-0.001	0.003	0.001	-0.003	0.000	-2.175	22	0.041
meanbl3 - meant316	-0.005	0.004	0.003	-0.045	0.035	-1.680	1	0.342
meanbl3 - meant334	-0.017	0.037	0.013	-0.048	0.014	-1.283	7	0.240
meanbl3 - meant325	-0.007	0.016	0.004	-0.015	0.001	-1.742	16	0.101
meanbl3 - meant32E	-0.011	0.029	0.008	-0.029	0.006	-1.381	12	0.192
meanbl3 - meant31A	-0.011	0.023	0.005	-0.021	-0.001	-2.311	22	0.031
meanbl4 - meant4	-0.001	0.003	0.001	-0.002	0.000	-1.631	22	0.117
meanbl4 - meant434	-0.021	0.049	0.017	-0.062	0.020	-1.219	7	0.262
meanbl4 - meant425	-0.010	0.021	0.005	-0.020	0.001	-1.980	17	0.064
meanbl4 - meant42E	-0.023	0.051	0.014	-0.053	0.007	-1.672	13	0.118

AR

	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t	df	Sig. (2-t)
				Lower	Upper			
meanbl1 - meant1	-0.0069	0.0236	0.0049	-0.0171	0.0033	-1.396	22	0.176
meanbl1 - meant116	-0.0220	0.0428	0.0214	-0.0901	0.0461	-1.028	3	0.379
meanbl1 - meant134	-0.0028	0.0032	0.0014	-0.0068	0.0012	-1.975	4	0.119
meanbl1 - meant125	-0.0017	0.0039	0.0009	-0.0036	0.0001	-1.985	19	0.062
meanbl1 - meant12E	-0.0241	0.0562	0.0162	-0.0598	0.0116	-1.484	11	0.166
meanbl1 - meant11A	-0.0125	0.0313	0.0067	-0.0263	0.0014	-1.866	21	0.076
meanbl2 - meant2	-0.0040	0.0148	0.0031	-0.0104	0.0024	-1.302	22	0.206
meanbl2 - meant216	-0.0118	0.0213	0.0106	-0.0457	0.0221	-1.106	3	0.350
meanbl2 - meant234	-0.0043	0.0081	0.0033	-0.0129	0.0042	-1.311	5	0.247
meanbl2 - meant225	-0.0213	0.0845	0.0176	-0.0578	0.0153	-1.207	22	0.240
meanbl2 - meant22E	-0.0108	0.0205	0.0055	-0.0226	0.0011	-1.968	13	0.071
meanbl2 - meant21A	-0.0080	0.0175	0.0036	-0.0155	-0.0004	-2.184	22	0.040
meanbl3 - meant3	-0.0020	0.0080	0.0017	-0.0054	0.0015	-1.173	22	0.253
meanbl3 - meant316	-0.0064	0.0123	0.0061	-0.0259	0.0132	-1.036	3	0.376
meanbl3 - meant334	-0.0019	0.0027	0.0010	-0.0044	0.0007	-1.786	6	0.124
meanbl3 - meant325	-0.0017	0.0066	0.0014	-0.0047	0.0012	-1.222	20	0.236
meanbl3 - meant32E	-0.0197	0.0501	0.0134	-0.0486	0.0093	-1.468	13	0.166
meanbl3 - meant31A	-0.0061	0.0143	0.0030	-0.0124	0.0003	-1.990	21	0.060
meanbl4 - meant4	-0.0019	0.0067	0.0014	-0.0048	0.0010	-1.364	22	0.186
meanbl4 - meant416	-0.0088	0.0170	0.0085	-0.0358	0.0182	-1.035	3	0.377
meanbl4 - meant434	-0.0010	0.0026	0.0011	-0.0038	0.0017	-0.971	5	0.376
meanbl4 - meant425	-0.0151	0.0592	0.0123	-0.0407	0.0104	-1.227	22	0.233
meanbl4 - meant42E	-0.0081	0.0182	0.0047	-0.0182	0.0019	-1.729	14	0.106

Bivariate Correlations

Variable 1	Variable 2	Pearson (r)	Sig. (2-tailed)	Description
EDA	1sr Derivative EDA valgus	0.516	0.014	Positive correlation between EDA and 1st derivative of valgus. First derivative helps to detect the events of EDA
EDA Varus	Pupil 2 alignment	-757	0.030	Negative correlation between EDA in varus and pupil when both aligned. This result exposes that as participant align both legs, the EDA response increases and pupil diameter decreases.
EDA Varus	Pupil 1 alignment	-750	0.032	Negative correlation between EDA in varus and pupil when one leg is aligned. This result exposes that as participant align one of another leg, the EDA response increases and pupil diameter decreases.
1st Derivative EDA Varus	Pupil 2 alignment	-828	0.021	Negative correlation between 1st derivative of varus and pupil when 2 aligned. This result exposes that as participant align both legs, the EDA response increases and pupil diameter decreases. Derivative reports EDA events.
1st Derivative 2 Alignment	HR Valgus	-600	0.011	Negative correlation between 1st derivative for 2 alignments and HR when in Valgus. This result exposes that as participant align both legs, the HR response increases and pupil diameter decreases.