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Using Augmented Reality for real-time feedback to enhance the execution of the squat

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Abstract

The importance of exercise and strength training has been emphasised, yet it is shown that the number of people who do not reach the average recommended hours of exercise has increased (WHO, 2020). Currently, a range of physical fitness products employs the use of technology. These products focus on providing engaging experiences but do not provide personalised real-time feedback to improve the execution of the exercise and reduce the risk of injuries. Hence, this research aims to explore the effectiveness of AR technology in providing real-time visual feedback for squat motion. Furthermore, which type of visual feedback is most effective for reducing errors in squat performance is also explored. This prototype includes a large screen that shows a mirror image of the participant as they perform squats with four different types of real-time visual feedback implemented. The motion of the participants was captured using the Kinect v2 system. This prototype focuses on giving feedback about the knee valgus error, which commonly occurs during the squat motion.

The four visual feedback types implemented are Traffic, Arrow, Avatar, and All-in-One. A user study with twenty participants was conducted to evaluate the feedback methods. The participants performed ten squats for each type of visual feedback, and their performance was measured with the frequency of the good, moderate, and poor squats they performed. A User Experience Questionnaire (UEQ) and a post-experiment interview were also conducted to measure their preferences and opinions regarding visual feedback. The results showed that Arrow outperformed the other conditions in terms of performance, followed by All-in-One, Traffic and Avatar. However, the majority of participants preferred Traffic, Arrow, All-in-One and Avatar in the descending order of preferences. The participants could further be categorised into two groups, a beginner and an advanced group. It was found that the beginner group preferred All-in-One, Arrow, Traffic and Avatar, in descending order. For the advanced group, in descending order, their performance ranked with Arrow to be best and followed by Traffic, All-in-One and Avatar. However, the majority preferred Traffic, followed by Arrow, Avatar and All-in-One.

The difference in performance results between the two groups can be attributed to the beginner group participants needing more information to improve their performance. In contrast, the advanced group benefits from a more straightforward and more intuitive visual feedback type since they already have sufficient knowledge. Future work could include a lateral view of the squat motion which would deliver more information to the user. Lastly, this prototype design can be extended to detect other types of errors users often perform during the squat motion or other strength training exercises or sports.

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Chapter 1
Introduction

The squat is known to be the most common exercise performed to enhance strength and conditioning (Hartmann, Wirth, & Klusemann, 2013; Hecker, Carlson, & Lawrence, 2019; Lin, Liang, Hsieh, Lin, & Wu). Although it is conventionally thought to be a lower limb focused exercise, the complexity of the exercise causes the whole body's muscles to be engaged, making it an effective exercise for general strength training (Lin et al.; Schoenfeld, 2010). The World Health Organization (WHO) has also emphasised the importance of strength training to improve life quality (WHO, 2020). Even though people are aware of the importance of strength exercises to improve health and life quality, there has been no improvement in the level of physical activity since 2001 (WHO, 2020). Many factors have influenced the level of physical activities (WHO, 2020) and getting injuries during strength training is one of the reasons why people lose interest or avoid the strength training (Hootman et al., 2001). The squat motion also poses a considerable risk of potentially severe injury if not performed correctly, such as muscle, ligament and disc rupture, spondylolysis and spondylolisthesis (Scholtes & Salsich, 2020). Knee collapse or knee valgus is one of the common mistakes during the performance of squats which can also cause serious injury (Tamura et al., 2017). In extreme cases, serious and long term knee injury can occur due to knee valgus due to the exercisers injuring their Anterior Cruciate Ligament (ACL) (Tamura et al., 2017). Mohr, von Tscharner, Whittaker, Emery, and Nigg (2019) showed that people with knee injuries such as ACL 3 to 12 years previously tend to have less contraction in their quadriceps and hamstring. This emphasises the importance of injury prevention since the muscle performance cannot return to its original level even after a long time in some cases.

Injuries are more common for beginners due to various reasons such as lack of proper technique, poorly maintained equipment, losing control of the weight and losing focus during exercise (Heshka & Jackson, 2015). Common ways to prevent injuries are for the individuals to observe themselves while exercising, get external feedback from trainers or learn the proper technique from training videos or exercise assistance technology (Klusemann, Pyne, Fay, & Drinkwater, 2012). Self-observation is one of the most common methods of injury prevention. In many strength training environments, exercisers are usually surrounded by large mirrors that provide instant visual feedback to check their form while they are doing strength training. However, if the exercisers do not have sufficient knowledge and experience in exercising, it could still lead to injuries (Hippocrate, Luhanga, Masashi, Watanabe, & Yasumoto, 2017). Thus, some people choose to utilise experienced professionals that can give feedback about the correctness of their exercise performance. However, this is often not readily accessible for many people due to cost or time-related limitations. Another way to prevent wrong execution is learning proper techniques through training videos but videos cannot provide any personalised feedback. Also, even though there are many states of the art devices such as Black Box VR Fitness, Tonal and Mirror that assist users during training, they all contain limited personalised visual feedback (Fitness, 2022; MIRROR, 2022; Tonal, 2022). The visual feedback from such devices is limited as there is no indication if the execution of the users' exercise is correct. Although users' feedback is bi-directional, as they can see themselves executing the exercise, it is still limited as there is no real-time feedback on the correctness of their movement. This prevents the users from identifying the errors that they are making. Therefore, providing instant visual feedback that advises the users on the correctness of their exercise performance is important to effectively prevent injury.

Augmented Reality (AR) is a technology that has been commonly used to provide real-time visual feedback and can be potentially used to provide real-time visual feedback during exercise. AR puts interactive digital components that emerge in the real world through a display such as a camera or a phone (Azuma et al., 2001); Milgram and Kishino (1994). It has been shown that AR technology has a high potential for providing useful feedback (Rekimoto & Nagao, 1995); Sekhavat and Namani (2018). For example, there are many fields where this technology is applied as a method of visual assistance, such as medical, education, entertainment and physical activities such as exercise, training and sports. (Alamri, Cha, & El Saddik, 2010; Guinet, Bouyer, Otmane, & Desailly, 2020; Tokuyama, Rajapakse, Yamabe, Konno, & Hung, 2019). Thus, due to its effectiveness, versatility and potential to provide personalized real-time feedback, this research considers AR as a means to provide feedback to users on improving squat motion by providing feedback about the detection and correction of the knee valgus error.

1.1 Research Questions

Following the above considerations, this thesis addresses the following research question:

"Can visual feedback using AR technology reduce mistakes during squat training?"

In order to answer the overall research, question the following five sub-questions are considered:

1. What are the characteristics of a correct squat execution?
2. What are the most common mistakes during a squat?
3. What kind of AR displays can be used for real-time feedback?
4. How can athlete's motions be captured during a squat exercise?
5. What kind of visual feedback can be provided on the execution of a squat?

These questions were answered through the process of designing and evaluation.

1.2 Contribution

The main contribution of this thesis is to provide personalised feedback to improve the execution of the squat motion by detecting the knee collapse error. Current exercise assistance devices cannot provide accurate, personalised feedback to the users, leading to incorrect execution of exercise by the user. Incorrect exercise execution, especially knee collapse during squats, can cause serious and long-lasting damage in the long term. This research found that the visual feedback using AR technology effectively decreases the users' error rate during the squat motion. Also, four different visual feedback types were implemented, and the most effective method to provide visual feedback was analysed by measuring errors in the squat motion performance of the participants.

1.3 Thesis Structure

The next chapter contains the background research on squat biomechanics, common errors during squats, motion capturing technology, general AR-based feedback and commercial exercise feedback products. The design process, system design, hardware setup and software development is described in Chapter 3. Then in Chapter 4, the user experiment section explains how the participants were gathered, how the information about their performance, the user experiment questionnaire and the post-experiment interview were gathered and the experiment procedure. The results of the user study are summarised in Chapter 5. This is followed by the discussion, conclusion and areas of future work sections.

Chapter 2
Background Research

Background research had been conducted to gain more information regarding the sub-questions raised in the introduction. Firstly, a thorough understanding of a proper squat form is required. Then a prevalent error that can occur during squats was studied and analysed. This information can later assist in building a prototype that can detect that error. Next, the state-of-the-art commercial products that assist the exercisers with visual feedback were studied, and their limitations and gaps were identified. Also, various motion tracking methods were researched. Lastly, research works that applied AR-based visual feedback in various contexts were studied.

2.1 Biomechanics of a Correct Squat

Correcting the users' squat motion requires a deep understanding of the biomechanics involved in a properly performed squat motion. The definition of squat is a closed kinetic chain exercise in which the force is transmitted through the body while the feet are fixed to the ground (Clark, Lambert, & Hunter, 2012). According to the findings, Schoenfeld (2010) discussed the biomechanics and kinematics behind the squat form and suggested the optimized squat form. The squat motion is one of the most common exercises to effectively enhance the whole-body strength and conditioning, especially for the lower extremity, if performed correctly (Hartmann et al., 2013; Hecker et al., 2019; Lin et al.). The dynamic squat is performed with the lifter initially standing up straight. Then, the lifter bends their hip hinge by flexing the hip and spine joint. The lifter then starts bending their knees until the appropriate squat depth is reached (Schoenfeld, 2010). The squat can be performed as deeply as the flexibility of the lifter's pelvic, knee and ankle joints allow, as there is no standardized squat depth that the lifter has to achieve (Schoenfeld, 2010). Once the lifter reaches the desired squat depth, they move up and return to the upright standing position by performing the motions in the reverse order of the downward part of the squat.

Although the squat is a practical exercise, it must be performed correctly to maximise its effectiveness and, most importantly, avoid injury. Some studies suggest that a squat that is too deep can increase the load on the knee, which leads to knee injuries (Thambyah, Goh, & De, 2005; Wilson, 1994). Another study also suggested this and recommended doing a quarter (knee angle of 110° to 140°) or a half squat (knee angle of 80° to 100°) to avoid excess stress on the knee which can cause potential injury. However, in a study done by Hartmann et al. (2013), the load distribution on the knee joint and the vertebral column was analysed depending on the squat depth. The previous papers that recommended a shallow squat to prevent injury were reviewed. They concluded that these studies faulted their analysis as they did not consider the mistakes exercisers made during a deep squat.

They claimed that a deep squat could enhance the strength of the lower extremity without causing injuries if the exercise is done correctly under experts' supervision. These findings emphasise the importance of having a proper form while performing squats which can be achieved by providing appropriate feedback to the exercisers.

2.2 Common Mistakes During Squats and Knee Valgus

As several types of possible mistakes can occur during squats, it is important to identify a common mistake that can potentially cause severe injury so that appropriate feedback to correct it can be provided. Many research works identified common mistakes during a squat. For example, heels are not fixed on the ground, rounded lower back, unstable knee position or knee valgus (Czaprowski, Biernat, & Kêdra, 2012; Hecker et al., 2019; Schoenfeld, 2010). These mistakes can negatively impact the exerciser while performing a squat. If the heels are not fixed to the ground, this reduces the body's stability during the squat (Czaprowski et al., 2012). Also, if the back is either extended or flexed excessively, the shear and compression force increases on the lumbar spine and if the knees are bent at an aberrant angle, such as during knee valgus, then the possibility of injury increases in the posterior and anterior cruciate ligaments (Czaprowski et al., 2012). Knee collapsing, dynamic knee valgus, and medial knee displacement all refer to the inward movement of the knees towards the midline of the body, which is considered one of the most common mistakes made while performing a squat (Almeida, França, Magalhães, Burke, & Marques, 2016).

Exercisers can be predisposed to having knee valgus during squats due to various reasons such as poor ankle dorsiflexion, fallen arches, weak hip abductors, quadriceps, hamstrings, core and calf muscles (Coelho, das Neves Rodrigues, Almeida, & João, 2021; Crowell, Nokes, & Cosby, 2021; Wilczyński, Zorena, & Ślęzak, 2020). This can lead to knee valgus occurring in various ways such as uncontrolled knee valgus on the descent (the eccentric portion of the squat), unilateral knee valgus on one side, continuous and extreme valgus, and extreme valgus during a regular body weight squat (MOTION RX, 2020). Here, extreme valgus refers to a situation where the inward movement of the knees happens to a large extent. When one of the aforementioned types of knee valgus is occurring, the exerciser needs to fix their form promptly because knee valgus could lead to serious injury if it is not corrected (Emamvirdi, Letafatkar, & Khaleghi Tazji, 2019); Scholtes and Salsich (2020); (Sheerin, Hume, & Whatman, 2012). Also, in extreme cases, the exercisers can injure their Anterior Cruciate Ligament (ACL) due to knee valgus (Tamura et al., 2017). Mohr et al. (2019) showed that people generally have decreased quadriceps and hamstring muscle contraction even 3 to 12 years after this type of injury. Thus, even though knee valgus is a common error, leaving it uncorrected can lead to injury that can cause long-lasting and severe consequences. These further emphasise the importance of effective real-time feedback mechanisms to allow users to promptly correct knee valgus.

2.3 AR Displays for Real-time Feedback

In order to provide effective feedback during squats, a technology through which real-time visual feedback can be provided. To develop such a feedback system, it is important to understand the characteristics of this technology and the current ways in which AR displays are used to provide real-time feedback. The usage of AR technology has improved rapidly because of its uniqueness, high interactivity and engagement with users (Silva, Albuquerque, & Medeiros, 2021). Guinet et al. (2020) demonstrated that one of the advantages of AR technology was how interactive visual feedback can support the users to be more engaged in the surrounding environment and motivate them to complete the given task. There are many fields where this technology is applied as visual assistance, such as medical, education, entertainment and physical activities such as exercise, training and sports (Alamri et al., 2010; Guinet et al., 2020; Tokuyama et al., 2019). For example, in the medical field, the real-time interactive digital elements in the real world encourage patients to undertake rehabilitation more easily (Alamri et al., 2010; Guinet et al., 2020). Also, using this technology in the medical and educational field is beneficial since it can illustrate parts that are often inaccessible in a real-life situation (Bianco, Celona, & Napoletano, 2018; Erazo, Pino, Pino, Asenjo, & Fernández, 2014; Meng et al., 2013).

Guinet et al. (2020) applied AR technology to provide visual feedback in a game that aids in rehabilitation for children with cerebral palsy. They recruited ten children with walking disabilities and used AR technology to gamify the rehabilitation. As a result, they found that all the participants could complete the rehabilitation and improve their walking performance. Furthermore, Alamri et al. (2010) showed how AR technology was used to aid the rehabilitation of patients suffering from poststroke. The study results showed that the patients were more motivated and engaged and had higher levels of enjoyment due to the AR visual assistance (Alamri et al., 2010). Another research used AR technology to encourage people to exercise their legs. They did this by building an AR framework where the participants can interact with digital elements using body movements (Tokuyama et al., 2019). A surgical training procedure with AR-based feedback was conducted, and real-life performance improved (Barresi, Olivieri, Caldwell, & Mattos, 2015).

A Magic Mirror is another form of AR that uses a big screen to project digital elements directly on the real objects, e.g. the human body or the surroundings (Bianco et al., 2018; Fiala, 2007). Ding, Huang, Lin, Yang, and Wu (2007) described that a Magic Mirror combines a mirror with a display that shows the artificial components that people can interact with. It consists of a plate of reflective glass, a Liquid Crystal Display (LCD) screen and a camera that can capture the real-world view and project it on the screen for interaction (Hauswiesner, Straka, & Reitmayr, 2011). When the brightness of the real-world side is greater than the side behind the plate of reflective glass, then the reflective glass mirrors the real-world image just like a normal mirror, while the screen side remains transparent. Therefore, when the LCD is turned off, the Magic Mirror operates like a genuine mirror. When the LCD is turned on, the Magic Mirror projects the image captured from the camera on the screen directly (Wang, Villamil, Samarasekera, & Kumar, 2012). This technology allows people to have instant visual feedback, allowing them to adjust to a fast-phase changing environment. Wang et al. (2012) showed that such technology can provide more effective visual feedback.

Some exercise assistance products have utilized AR technology. Tonal, Tempo, and Mirror are state of the art products that can provide visual information and assist users in their workout. Their products consist of a big smart screen so the users can see their reflections and watch the virtual trainer's movements and follow (**Figure 1**).

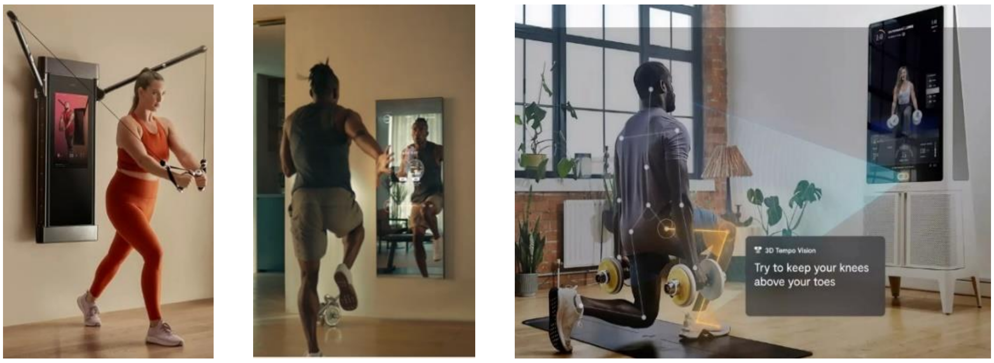


Figure 1 Tonal, Mirror and Tempo (From left to right)

For Tonal, the exercise is shown on the screen so the users can follow, but the interaction is only one way from the device to the users (Tonal, 2022). Thus, there is no personalised or real-time feedback to the users (Tonal, 2022). The product of Mirror has a simpler design with a similar purpose, except this product is based on bodyweight exercises (MIRROR, 2022). It is a large smart touch screen with a built-in camera to track users' body movement (MIRROR, 2022). However, the camera only measures the number of repetitions and speed of users' movement, which does not provide any informative feedback on their posture (MIRROR, 2022). However, Tempo Fitness provides more personalised feedback by using a front camera used to build a 3D body model of the user (Tempo, 2022). Then the 3D model is used to analyse the form of the user, and the human online trainer advises the user on their posture (Tempo, 2022). This product's limitation is that the feedback is only available when there are online trainers. Also, the posture feedback is only based on the front view of a 2D image, so the analysis of the performance is restricted (Tempo, 2022).

The mentioned studies emphasised the effectiveness of utilising visual feedback from AR technology in a range of applications and supported the idea that people's engagement levels increase while using it. This makes AR an effective feedback medium for fitness-related applications. However, a significant limitation of the current high-technology exercise assistance equipment is that they do not provide personalised feedback in real-time. Hence, this research is focused on addressing this gap by providing personalised visual feedback in real-time using AR technology so the users can correct their errors during performance instantaneously.

2.4 Body Tracking and Motion Capturing System

In order to provide effective AR-based real-time and personalised visual feedback during squats, a motion capture system is required to analyse the users' movements in real-time. This is supported by a study done by Sekhavat and Namani (2018), where it is mentioned that for a satisfactory user experience in using AR to interact with digital components on a screen with their body, high precision body motion capturing is required. However, several research works have indicated that for AR-based visual feedback methods such as Magic Mirror, body motion tracking is the most important and challenging process to implement since the virtual image must be interactive with the reflection of the moving body parts and give correct visual feedback (Hauswiesner et al., 2011; Wang et al., 2012).

Thus, many different motion capturing technologies were explored to find the most suitable system for this research. Many studies used motion capture for various tasks such as analysing golf swinging motion, martial art movement and lip motion synchronising (Hegarini, Mutiara, Suhendra, Iqbal, & Wardijono, 2016; Noiumkar & Tirakoat, 2013; Patoli, Gkion, Newbury, & White, 2010). Sato and Cohen (2010) noted that generally, the motion capturing technology can be categorized into three types according to the main sensing source used which are mechanical, optical and electromagnetic. They then identified each type of motion capturing tool's merits and demerits. Firstly, mechanical motion capture uses devices attached to the human body so the body motion can be tracked by modelling the path of the devices. Its advantages are that it does not face interference from external sources of magnetic fields or light. However, the system is unaware of the orientation of the person it is tracking. Hence, the information from the trackers has to be supported by other types of sensors (Sato & Cohen, 2010).

Optical sensing also requires people to wear a suit with markers attached and multiple infrared cameras. It is beneficial since people's movement is not restricted by cables and other equipment. However, the downside of this technology is that it is costly. Wearing the suit can cause an uncomfortable experience for the user and the tracking information can be lost if other people or objects are blocking the view of the camera (Sato & Cohen, 2010). Finally, magnetic motion tracking's advantage is that it can be set up relatively inexpensively. Also, there is no loss of information due to interference from people or objects. However, this setup also restricts people's movement due to the requirement that cables need to be attached to the users. Sato and Cohen (2010) enquired the users about their experiences while using the three types of motion tracking. They concluded that the motion capturing systems that restrict movement were not favoured by the users. Hence, non-restrictive motion-capture tools using optical sensing are more suitable for this research as the users should be able to freely move while performing physical activity such as squats.

Microsoft Kinect is one such example of an optical sensing-based body tracking system, which is low-priced and has been widely used in many applications. Kinect v1, Kinect v2 and Azure Kinect are the prominent versions of Kinect that exist in the market. They have similar hardware and software, but the motion capture resolution increases from Kinect v1 to the newest Azure Kinect model. As shown in **Figure 2**, the hardware parts of Kinect are composed of an RGB camera, depth sensor and a four-directional microphone which enables Kinect to process RGB and depth sensing and audio signal at the same time (Lun & Zhao, 2015).

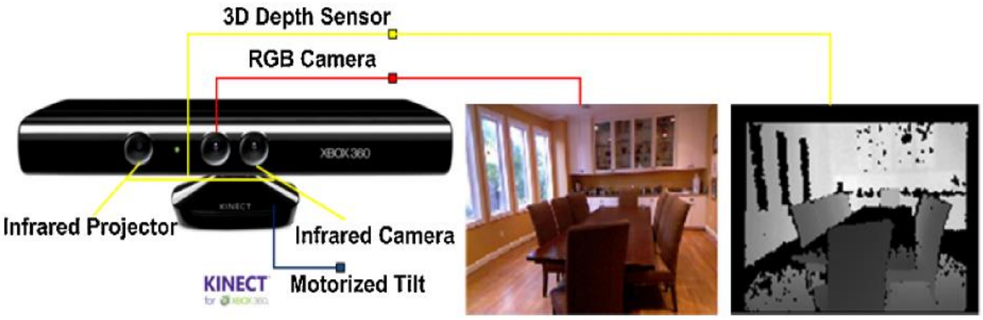


Figure 2 Kinect Composition

Kinect systems can obtain depth information by emitting infrared rays which are reflected from objects and received by the depth sensor. The depth calculation is based on the time between emitting the IR ray from an IR laser diode and receiving the reflection. The sensor then constructs the depth frames for an image from the received depth information. The skeletal structure is then predicted from the depth and colour image data using a pre-trained machine learning model (Lun & Zhao, 2015). The skeletal joint positions are then inferred from the predicted skeleton structure.

Due to this accurate and low latency depth estimation and machine learning-based skeletal structure prediction, Kinect has high precision in real-time motion capturing. Furthermore, Kinect can synchronise visual signals, capture human 3D movements, detect human faces, and recognise human speech, among other things (Corporation, 2014). Lun and Zhao (2015) mentioned that this technology has the protentional for usage in many fields such as healthcare, education, training and 3D reconstruction. Han, Shao, Xu, and Shotton (2013) reviewed Kinect's framework and algorithms for each of its functional contributions such as object tracking & recognition, human activity analysis, hand gesture analysis, and indoor 3D mapping. This review indicated that due to the low-cost and simple set-up required to use Kinect's functionalities, it is a useful tool for researchers and engineers that require functionalities that Kinect offers.

All the Kinect versions share the mentioned basic capabilities, but they differ in terms of motion capture resolution. Kinect v2 was developed based on Kinect v1 with an improved depth-sensing technology that has higher precision and a higher resolution in the RGB image camera (Tölgyessy, Dekan, Chovanec, & Hubinský, 2021). Kinect v2 provides substantially superior depth information compared to Kinect v1 (Lun & Zhao, 2015). Tölgyessy, Dekan, and Chovanec (2021) evaluated the performance of Azure Kinect by comparing its skeleton model tracking ability against Kinect v1 and v2. The result indicated that the precision and accuracy of Azure Kinect were better than that of Kinect v1 and Kinect v2. This was further supported by Albert et al. (2020), they compared Kinect v2 and Azure Kinect by measuring pose tracking performance for the participants' gait. The gait analysis was done using both Kinect v2 and Azure Kinect and the result was compared with the gold standard of the Vicon multi-camera motion capturing system and 39 marker Plug-in Gait model. The result of the experiment showed that the Azure Kinect has a better motion tracking algorithm and can achieve higher accuracy in gait parameters in 3D space when compared to that of Kinect v2. This shows Azure Kinect has the advantage of high accuracy and precision in constructing a skeleton model of the user compared to that of Kinect v1 and Kinect v2.

The following research works demonstrate the effectiveness of Kinect systems applied to body motion tracking based tasks. R. A. Clark et al. (2012) used Kinect v2 to assess the postural control and validated the usefulness of Kinect in research by comparing the results of traditional manual techniques to that of Kinect v2. The postural control could not be quantified previously but since Kinect could provide joint coordinates in three-dimensional space, the performance could be measured. R. A. Clark et al. (2012) collected 20 subjects for three postural control tests. Their motion was captured using Microsoft Kinect v2 and analysed using a multiple-camera 3D motion analysis system. R. A. Clark et al. (2012) found that the results validated the use of Kinect for posture assessment. All the mentioned research works show that Kinect can be used for accurate motion capture and analysis, which is an important characteristic of a real-time and personalised feedback system to have.

2.5 Visual Feedback Types

In an AR-based system that provides visual feedback to correct errors during the squat performance, various types of information can be provided as feedback, and it is useful to understand the possible options that could be utilised. Thus, the following research works were reviewed to explore different types of visual feedback that they utilised and find how effective the feedback was. In an article written by Horschig and Sonthana (2017), they used an arrow indication to effectively and straightforwardly illustrate knee collapse during squats for educational purposes. Sekhavat and Namani (2018) used projection-based AR technology to assist in gait rehabilitation, where footsteps were projected on a treadmill and the patients were encouraged to match their gait to the projection. Sekhavat and Namani (2018) compared the performance of the participants on rehabilitation tasks by using projection-based AR and normal monitor-based feedback. The result of the research showed that AR projection feedback resulted in improved performance on the given tasks. Murray, Hardy, Spruijt-Metz, Hekler, and Raij (2013) showed that using an avatar for mobile health applications can enhance the interactivity of the experience since body gesture communication plays an important role in intuitively delivering non-verbal information. The use of colour also serves as one of the primary visual feedback methods and Shen, Ong, and Nee (2009) used colours as an indication of performance status.

From the research done about visual feedback methods, the commonly utilized visual feedback methods identified were arrow indication, projection, avatar and colour. Projection-based feedback is less applicable for the task of error detection feedback in squats as the exercisers need to be able to see their movements in conjunction with the visual feedback. However, in projection-based methods, the feedback information is projected onto real-world objects. On the other hand, arrow, avatar and colour-based feedback can be displayed on a screen which could allow the user to see the feedback in conjunction with their movements. Text-based visual feedback was not reviewed as it conveys the same semantic meaning as arrow, colour or avatar-based feedback.

Research works about the application of different visual feedback methods were reviewed to understand what kinds of visual feedback methods there are and how they affect users' performance in various applications. These research works show that adding visual feedback results in improved performance by the users on the given task. This emphasises the usefulness of incorporating visual feedback to improve squat performance. Out of the various feedback methods reviewed, arrow indication, avatar and colour based visual feedback methods would be most suitable for the execution of squats.

Chapter 3
System Overview

The previous chapter identified a gap in the current research and technology's capability to address users' needs from our background research and brainstorming. Common mistakes in squatting exercises have been described, and related injuries were explained. It was found that incorrect exercise execution can lead to injuries that discourage people from doing strength training. Throughout the design process, we used the user-centric design approach to guide the development of the system prototype. We established the design requirements in consultation with professional personal trainers and physiotherapists. Once the essential components of the prototype design have been established, we developed our prototype with iterative feedback from the personal trainers, physiotherapists, and HCI researchers throughout the development process. In the remainder of this chapter, we present the design considerations and requirements in subsection 3.1, our system prototype design in subsection 3.2, hardware and software implementation in subsection 3.3, squat motion tracking and calibration in subsection 3.4, and visualisation techniques in subsection 3.5.

3.1 Design Considerations and Requirements

This overall research aims to determine whether real-time visual feedback in Augmented Reality (AR) can assist exercisers in improving their squatting performance by detecting mistakes and helping reduce the risks of injury. In order to fulfil our goal, we further asked four questions to guide the framing of our design requirements: i) what are the characteristics of a correct squat execution? ii) what are the most common mistakes during squat training? iii) what kind of AR visualisation system can be used for real-time feedback? and iv) how can we capture the exerciser's motion during the training? These let us to three design requirements as follows:

R1) **Detection of Knee Valgus** - The first design requirement is that the system should be able to monitor the exercisers during their training and detect the occurrence of knee valgus, the knee's inward collapsing. This is because background research had identified that knee valgus, is one of the most common mistakes during training.

R2) **Spatial Overlay** - The second design requirement is to provide real-time and personalized feedback, which visually communicates the information and overlays such information spatially for the exercisers. Although commercial products with visual feedback exist to assist people in improving their performance in strength training, they also have drawbacks as they provide limited real-time feedback (MIRROR, 2022; Tempo, 2022; Tonal, 2022).

R3) **Unobtrusive Body-Tracking** - The last design requirement is that the system should be able to perform full-body tracking without requiring the exercisers to put on a tracking suit or place markers on their body. This narrows the solution down to a vision-based detection system.

3.2 System Prototype Design

Based on the three design requirements, we proposed the three areas of focus for our implementation: 1) the detection of the exerciser's movement from the frontal view, 2) using a large display to provide visual feedback, and 3) using an RGBD sensor (Kinect v2) for a full-body tracking for their low-cost and unobtrusiveness.

Frontal View – From our preliminary testing with the RGBD sensor's capability to detect the user's movement from the frontal, lateral, back, and diagonal view, we found that knee valgus was best detected from the frontal view. In the lateral view, whether it was from the left or right side, the nearer leg occluded the other leg causing errors in the pose estimation of the body. However, the lateral view was suitable for detecting the issue of heels off the ground while squatting, which is another common issue in squat training. The back view could be used to detect knee valgus; however, it did not work as well as the frontal view due to the limitation of the pose estimation algorithm. We speculate that the algorithm has been trained to bias toward better prediction of the frontal view. Finally, we have also tested the diagonal view where the users oriented themselves 45° to the RGBD sensor. This allowed us to detect both knee valgus and heels-off the ground issues, but the detection did not work as well for the frontal or lateral view. Because of our focus on detecting knee valgus, we decided that it would be best to maximise the precision of the frontal estimation using the frontal view rather than the diagonal view to support lateral pose estimation.

Magic Mirror – To provide the exercisers with visual feedback, we have considered several Augmented Reality (AR) technologies to allow the spatial overlay of visual information. We have decided to adopt the Magic Mirror approach, which combines a large screen display with a camera feed to provide real-time overlay of information onto the exerciser's virtual image appearing on the screen in front of them as if it is a mirror. This is a conventional method that exercisers typically train and have been shown to work well by previous research (Hippocrate et al., 2017). With the Magic Mirror, visualisation information can be projected onto the exerciser's body in real-time at the locations of interest that require their immediate attention. We have designed and developed four types of visualisation techniques for our Magic Mirror for squat training, and this will be covered in section 3.4. The size of the screen and the distance of the screen placement from the user play an important role in the overall experience where a one-to-one mapping between real and virtual is desirable, and we will provide more details in section 3.3.

RGBD Sensing – For body tracking, we considered various technologies mentioned in subsection 2.4. Although mechanical and electromagnetic motion capture devices can provide high precision tracking, their drawbacks were their obtrusiveness, affordability, and tedious calibration process. For this research, we preferred a relatively low-cost, easy to set up, and the least intrusive solution to track the exerciser's activity. The RGBD sensor was the most obvious choice for us as it utilises optical sensing to provide both colour and depth information for visual feedback and robust pose estimation of full-body movements. We will explain our procedures for calibrating the users for our squat training program in section 3.5.

3.3 Hardware and Software Implementation

Figure 3 illustrates the system overview comprises the user (exerciser) standing in front of a backdrop facing an RGBD sensor mounted screen, which connects to a PC. For the display, we used a 55-inch television screen set up in portrait orientation to mimic a full-body mirror used for exercise activities. For the RGBD sensor, we have access to the Microsoft Kinect Version 2, which had been mounted below the screen. The Kinect was used to detect and track the exerciser's 3D skeletal and capture the video feed. A black backdrop was placed behind the participants to prevent visual artefact in the background that could interfere with the Kinect's tracking.

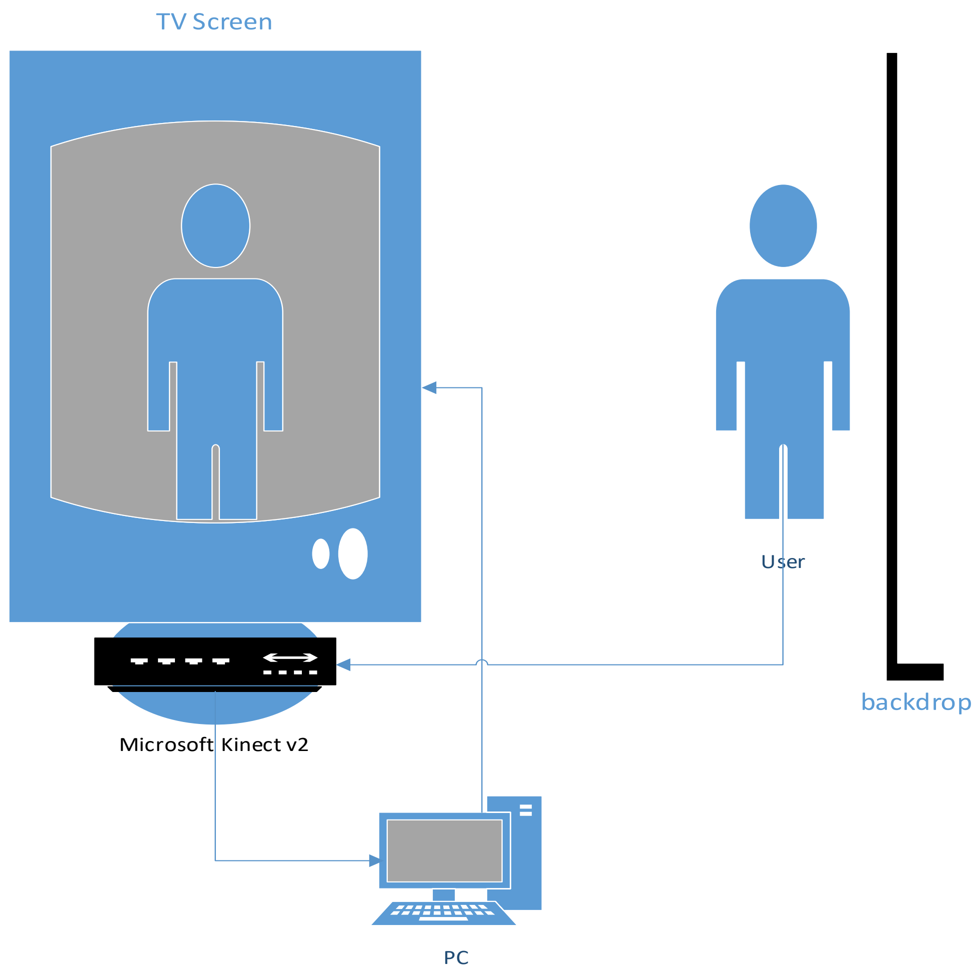


Figure 3 System Overview

Our setup required that the user stands approximately 2 meters in front of the Kinect-mounted screen. This location had been marked on the floor to help the participants maintain their distance from the screen. This distance was within the optimal tracking range of the Kinect (i.e., 0.5 to 4.5 m). Furthermore, on average, the participant should fit within the screen frame. **Tables 1** and **2** show the specification of hardware and software used, respectively.

Table 1 Hardware Specification

Hardware	Type	Specs
PC	CPU Ram Graphic Card Operating System	Intel(R) Xeon(R) CPU E3-1240 v3 @3.40GHz 16Gb NIVIA GeForce GTX750 Windows 10
TV	Model Dimensions with Stand Screen size Resolution Backlight Type	55" (139cm) 4K ULTRA HD WEBOS SMART TV 1232mm (Width) * 782mm (Height) * 260mm (Depth) 55" (139cm) 3840 x 2160p LED
Kinect v2	Audio Motion sensor RGB Camera Depth camera Method Depth camera Resolution Data Power Synchronization Dimensions Mass Mounting	4-mic linear phased array 3-axis accelerometer 1920 x 1080 px @30 fps Time-of-Flight 512 x 424 px @ 30 fps USB 3.1 gen 1 External PSU RGB & Depth internal only 249 x 66 x 67 mm 970 g One ¼-20 UNC

Table 2 Software Specification

Software	Version
Unity	2020.3.22f1
OBS Studio	27.0.1
Visual Studio 2019	16.11.4
Kinect SDK 2.0	2.0.1410.19000

3.4 Squat Motion Tracking and Calibration

The purpose of the system is to evaluate the exerciser's performance during their squat training on how well they can perform their routine, more specifically, detecting if knee valgus occurs. In order to evaluate knee valgus, the exerciser's lower body is analysed using the skeletal joints coordinate data provided by the Microsoft Kinect. This information varies for different exercisers depending on their body structure, body flexibility, forms, and preferred stances. Therefore, the optimal pose for each individual would differ. Hence the constraints for joint coordinates must be personalised. The calibration process prior to the usage of the system is crucial for the accuracy of the evaluation outcome. **Figure 4** illustrates a flowchart outlining the calibration process and the evaluation procedure of the squat routine.

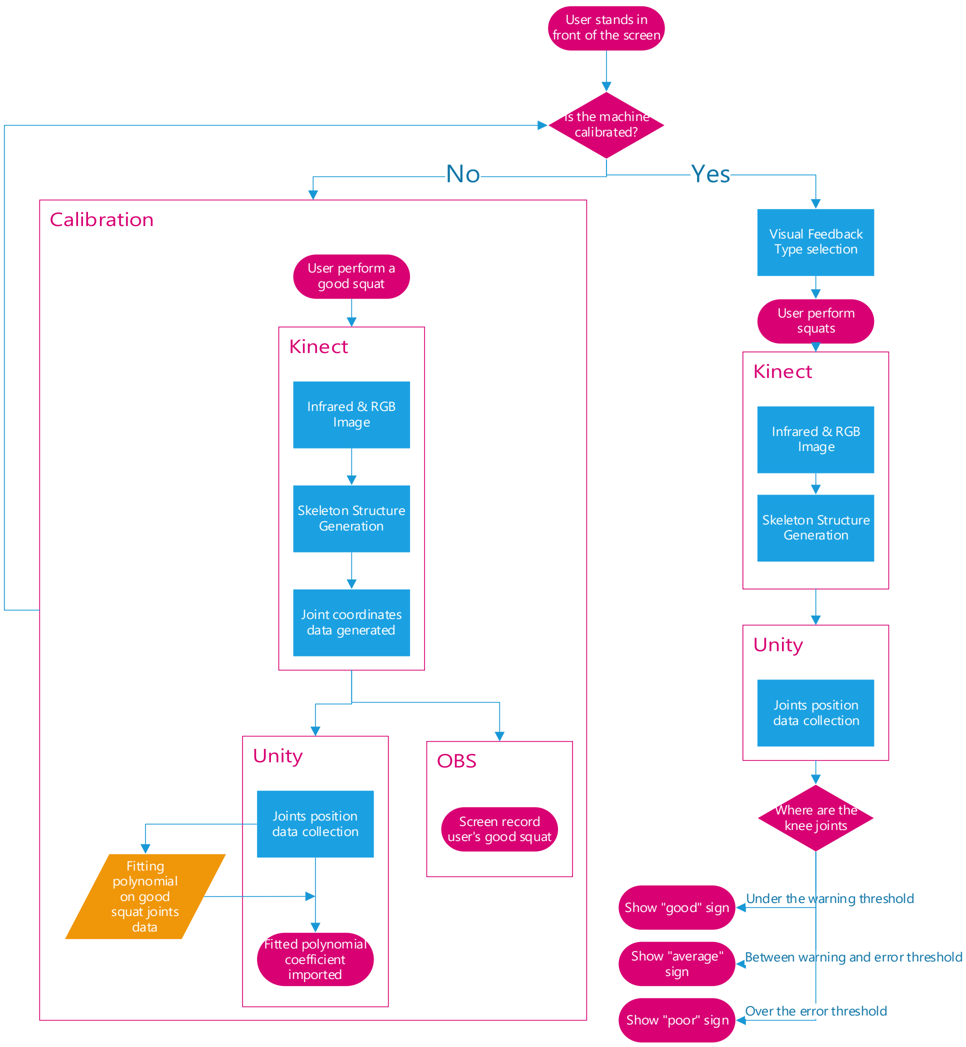


Figure 4 Calibration Flow Chart

To begin the calibration process, the exerciser stood at the marked spot, which was approximately 2 meters in front of the screen. The video showing the correct squat execution was then played for them to follow. The system uses Microsoft Kinect to track their skeletal model and joint positions, which are continuously recorded as they perform a squat. This recorded joint coordinate data of the correctly executed squat is then used as a baseline. Knee collapse happens when knees bend inwards, vertically passing the ankles at the high depth of the squat. Hence, the distance between the knee joints can be compared to the distance between the ankle joints to detect knee collapse. A ratio was calculated by dividing the distance between the ankles by the distance between the knees. The measured distance between the knees and the distance between the ankles are shown in **Figure 5**.

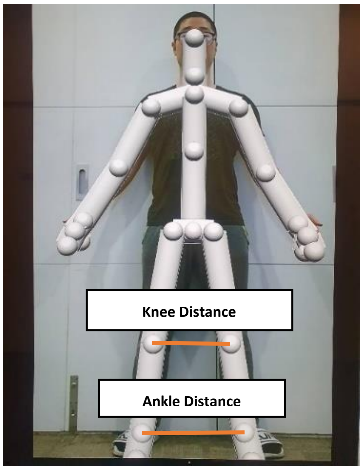


Figure 5 Knee Distance and Ankle Distance

Nevertheless, the knee distance is usually less than the ankle distance in the normal standing pose, which is also true for the initial beginning stages of the squat. Therefore, the knee angle must also be monitored at different stages of a squat routine. The measured knee angle is shown in **Figure 6**. Since the angles are symmetrical, the left knee angle was recorded for the prototype.

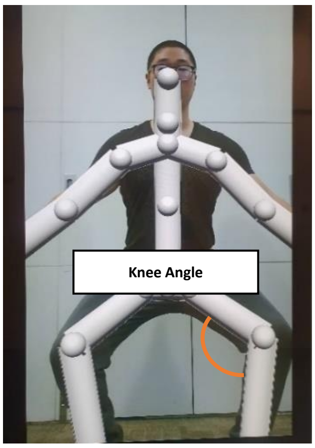


Figure 6 Knee Angle

From observation, it is safe to presume that the knee angle decreases as the user lowers their body during a squat and increases as they stand back up. **Figure 7** shows the example recording of five sampled values of the ratio between the distance of the knees and the distance of ankles (top) and knee angles (bottom) of good squat form from the beginning to the end of the squat.

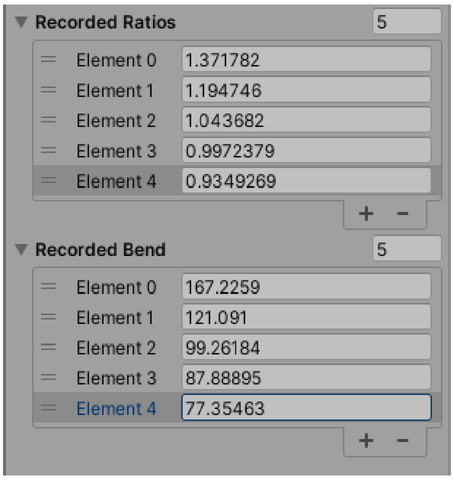


Figure 7 Recorded Sample Data of Good Squat

For example, a few values of the ratios in a good squat are 1.37, 1.19, 1.04, 1.00 and 0.93. These values were recorded at the knee angles of 167°, 121°, 99°, 87°, and 77°, respectively. If knee collapse occurs at a given stage of the squat or knee angle in the subsequent squats, the ratio will be bigger than that of the good squat at that knee angle.

However, since the recorded values are not continuous, the recorded knee angle and ratio values were then imported into Excel, treated as the x and y coordinates, respectively and plotted on a graph. A second-degree polynomial was fitted on the data points of this graph. This polynomial allows us to predict what the ratio should be if the user performs a good squat at a given knee angle. Thus, when the user performs a squat again, if their ratio values are greater than the curves at the corresponding knee angle, this would suggest that they are not performing a good squat at that moment. Thus, this polynomial can be used as a threshold to classify the user's movements that are considered *"good"* performance comparing to the calibration.

Nevertheless, just predicting if a squat is good or not does not provide information about the degree of the incorrectness of the squat. Thus, it is useful to add an intermediate category for classifying the cases when the incorrectness in the squat. We introduce the *"moderate"* to represent the averagely performed level of knee collapse. This can be done by treating the curve generated above as a threshold between *good* and *moderate* squats (served as the warning threshold) and constructing a new threshold curve to distinguish between *moderate* and *poor* squats (served as the error threshold). This was done by multiplying the ratio values of the warning threshold curve by 1.15, creating a tolerance region between good squats and poor squats, where the squats are classified as moderate. This tolerance level of 1.15 was chosen by trial and error, by incrementally increasing it until the predictions did not sporadically jump between each category and there was a smooth change window between the good, moderate, and poor squat categories depending on the level of knee collapse (shown in **Figure 8**). Then the fitted

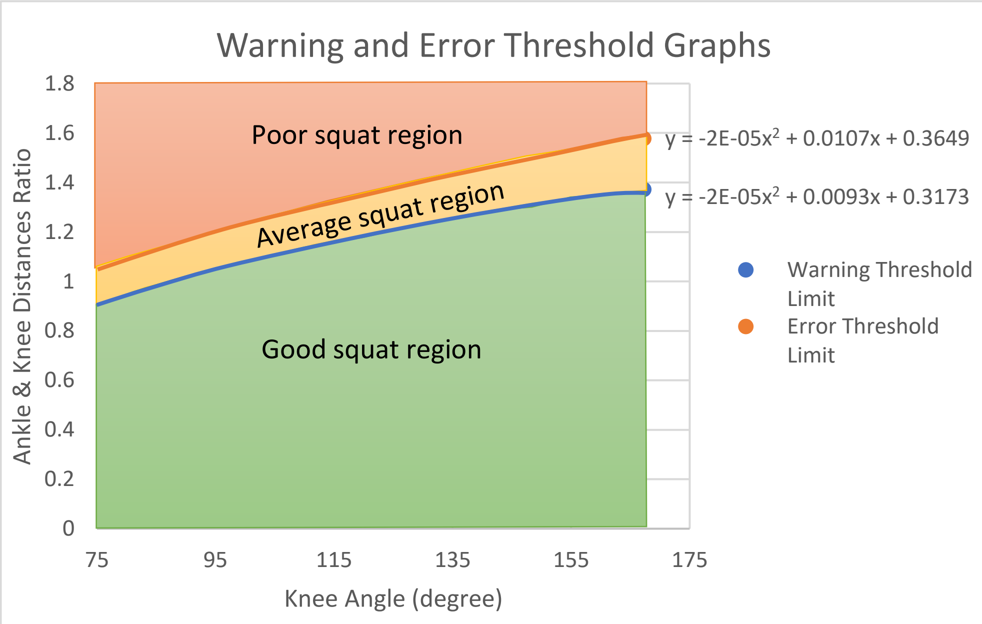


Figure 8 Graphs of Average (Blue) and Poor (Orange) Threshold and Equations

coefficients of the curves were inserted into the code. The users' future squat ankle-knee distances and knee angles were compared against these curves to determine when knee collapse occurs (Shown in **Figure 9**).

```
#region Error Threshold
thresholdRatio = -2 * Mathf.Pow(10, -5) * Mathf.Pow(leftBend, 2) + 0.0107 * (leftBend) + 0.3649;
#endregion

#region Warning Threshold
AlarmRatio = -2 * Mathf.Pow(10, -5) * Mathf.Pow(leftBend, 2) + 0.0093 * (leftBend) + 0.3173;
#endregion
```

Figure 9 Machine Calibration

Once the calibration was done, the visual feedback type was selected, and the user started performing squats independently. Real-time feedback was provided according to the selected method. Kinect collected the joint coordinates and compared them with the threshold curves previously obtained to give the researcher the evaluation of the user's performance. If the joint data lay under the warning threshold which was the good squat's curve, the squat was evaluated as *"good"*. If the data lay between warning and error threshold curves, then it was evaluated as *"moderate"*. Finally, if the data was over the error threshold, then it was evaluated as *"poor"*.

3.5 Visual Feedback Design

The goal of providing the exercisers with visual feedback was to inform them of their real-time performance and guide them in each repetition throughout the training session. The various feedback types were designed to alert the user in different ways when an error occurs while they are performing squats. Considering section 2.5, it was decided that indication by the colour, arrow and human avatar will be provided for the visual feedback. Moreover, the combination of all these visual feedback types is also used as one of the visual feedback methods to see if providing different types of visual information at once helps to reduce errors in squat performance.

The visualisation methods were categorised into corrective and preventive approaches. This was done to see if there is a difference in the effectiveness of reducing errors in squat performance between the visual feedback methods of the two categories. The traffic light is a corrective approach to inform the users using red, yellow, and green lights along the border to indicate the presence of an error without description or spatial annotation to specify the exact location. Another explicit corrective informing method is using an arrow indication which provides a spatial annotation as well as the direction and magnitude of the adjustment required to fix an error. Avatar is an implicit preventive approach to guide the user to follow the movement of an overlapping semi-transparent video recording of a correctly performed squat by the participant. All-in-One is a combination of all visual feedback types (Traffic + Arrow + Avatar), which was added last to compare whether the combination of corrective and preventive approaches can achieve better performance than each feedback method by itself.

Therefore, the final prototype is developed to provide four different types of personalised visual feedback: Traffic light, Arrow indication, Avatar and All-in-One. Each visualisation mode requires the calibration data, which is obtained for each user to evaluate the squat performance and be used in feedback methods for error detection according to the procedure outlined in Section 3.4.

The border colour is set to black at the beginning for the Traffic light visual feedback. When the participant is performing a good squat, the colour changes to green. If the participant starts to bend their knee inwards and the joint positions exceed the calibrated warning threshold, it shows yellow light as a moderate sign. This moderate category was introduced in the traffic sign visual feedback method to provide more continuous feedback to the users. If the knee goes beyond the pre-set error threshold, it shows a red sign as an error. Participants can see the colour change during the procedure (**Figure 10**).

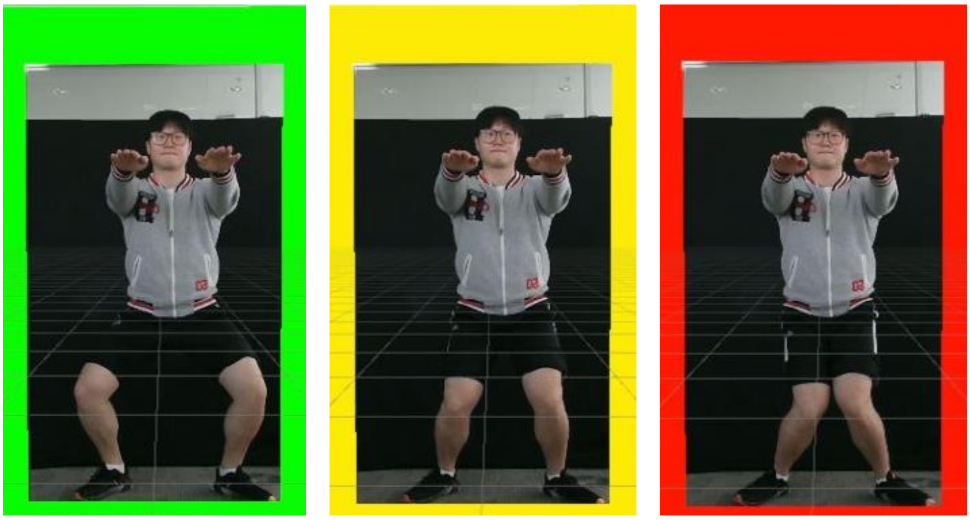


Figure 10 Traffic Visual Feedback

There is no visual feedback for the Arrow type if the user already performs good squats. However, two arrows appear beside the knees and point outwards when the knees' joints coordinate go beyond the set warning threshold. The further knee goes inside, the bigger the arrows get. When the user fixes their knee position according to the visual feedback, then the arrow pointers disappear. (**Figure 11**).

Figure 11 Arrow Visual Feedback

For the avatar visual feedback, A correctly performed squat was recorded using a screen recording software called OBS at the beginning of the experiment. The recorded video is overlaid on the screen with reduced opacity so that the participant can try to match their form to their avatar or overlaid video (**Figure 12**).

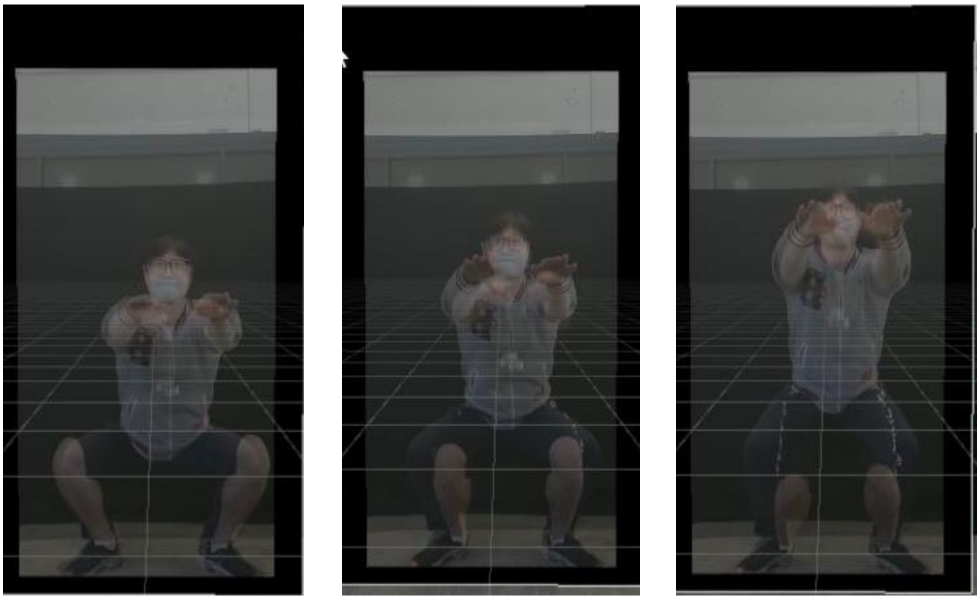


Figure 12 Avatar Visual Feedback

Finally, the All-in-One visual feedback is implemented by enabling all of the previously implemented feedback types to be displayed (**Figure 13**).

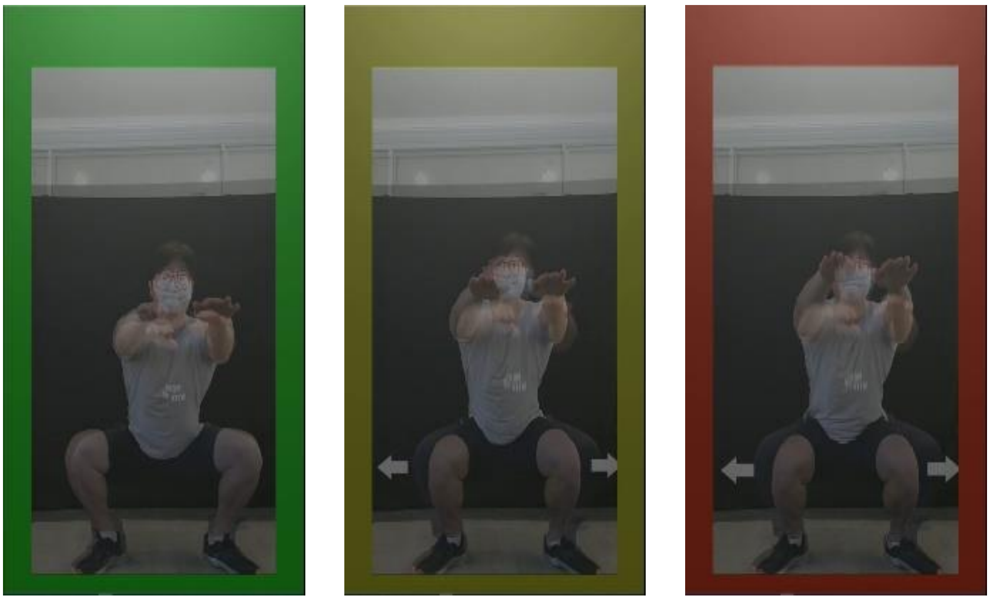


Figure 13 All-in-One Visual Feedback

Chapter 4
User Study

A user study was done to find whether AR-based real-time visual feedback helps users to improve their performance during squats by reducing the number of errors. If so, the effectiveness of the visual feedback types can also be compared according to the user study results. For the user study, the participants were collected, and their demographic information was analysed. Three modes of measurements were collected: performance, post-experiment interview and User Experiment Questionnaire (UEQ). These modes were collected as they provide information about different aspects of the visual feedback methods. The performance measurement shows the objective effectiveness of the feedback types and the post-experiment interview, and the user experiment questionnaire shows the subjective preference of the users. The information about the participants, measurements, and the user study procedure is described in detail in the following sections.

4.1 Participants

We recruited twenty-four participants, twenty males (*mean ± SD:* age 25.1 ± 4.4 years, body: ± 12.8 kg, height: 176.3 ± 8.2 cm) and four females (*mean ± SD:* age 24.3 ± 4.6 years, bodyweight: 74.0 ± 15.0 kg, height: 167.0 ± 9.5 cm). They consisted of 12 Beginners, nine intermediates, and three experts. Beginners were defined as people who have never trained or have been taught before in physical exercise execution. Intermediate category participants were defined as the people who have been taught or trained but do not have a stable performance or make frequent mistakes. Experts are defined as people who are comfortable doing squats in the correct form by themselves without making many mistakes. Given these definitions, the participants self-identified themselves in these categories.

4.2 Measurements

The study's goal is to find whether the AR real-time visual feedback reduces mistakes during squat training. Measurements are done in three different aspects: Performance, Post-experiment interview and UEQ for all participants in the study. The performance measurement involves evaluating each squat as good, moderate or poor according to the procedure outlined in Section 3.5. After this performance evaluation, the number of good, moderate and poor squats performed for each visual feedback is compared to the no visual feedback setting. Hence, this comparison can identify whether visual feedback helps reduce errors during the execution of squats. Furthermore, the visual feedback types can be ranked according to their performance measurement results, providing further information about which visual feedback is the most effective.

A post-experiment interview and UEQ measurements were carried out to gain further information about the user experience with the visual feedback methods. This information can be used to understand the strengths and weaknesses of the visual feedback methods. In addition, this can help discover the underlying reasons why some visual feedback methods might lead to a better squat performance in the users. Therefore, after the experiment, a post-experiment interview was done to find which feedback people personally preferred the most. Also, a UEQ was done, which allowed information about other aspects of the user experience to be collected. Lastly, the experience level of the participants was considered during the analysis for all measurements. This can provide insights into how the performance and preference measurements might differ between the visual feedback types depending on the users' experience level.

4.2.1 Performance Measures

Quantitative measurements about the squat performance are obtained by counting how many good, moderate, and poor squats the participants do while performing ten squats for each visual feedback. Participants also did ten squats in a controlled setting when no visual feedback was provided apart from their mirror image. The threshold curves classify the squats described previously, and a colour indicator is used to inform the researcher about the squat classification. This information is available for each squat performed for each feedback type to the researcher only. The participants cannot see the evaluation of their squat, as the only information they have access to is the visual feedback provided in the prototype. Although the traffic light visual feedback essentially uses the same threshold curves as the squat evaluation to provide the red, yellow and green indications, the users are not made aware of the evaluation process and just treat the colours as visual feedback information. The squat performance for the visual feedback types concerning the control setting and for each other is analysed to evaluate their effectiveness.

4.2.2 Post-experiment Interview

A post-experiment interview was done after the participant completed the squats for all visual feedback types.

The interview questions were:

- "If you rank the visual feedback modes, how would you order them?"
- "What was good about the best visual feedback type and what was poor about the worst visual feedback type?"
- "Do you have any further improvements or suggestions?"

4.2.3 User Experience Questionnaire

A questionnaire was done for each visual feedback type using the UEQ, which is a verified user experience questionnaire. The UEQ assesses the quality of a system along six dimensions, including 26 questions using a 7-point Likert scale. Each category focuses on feedback for one aspect of the prototype and includes scales that allow the users to provide feedback on various prototype attributes by scoring. The structure of the UEQ is shown in **Figure 14**.

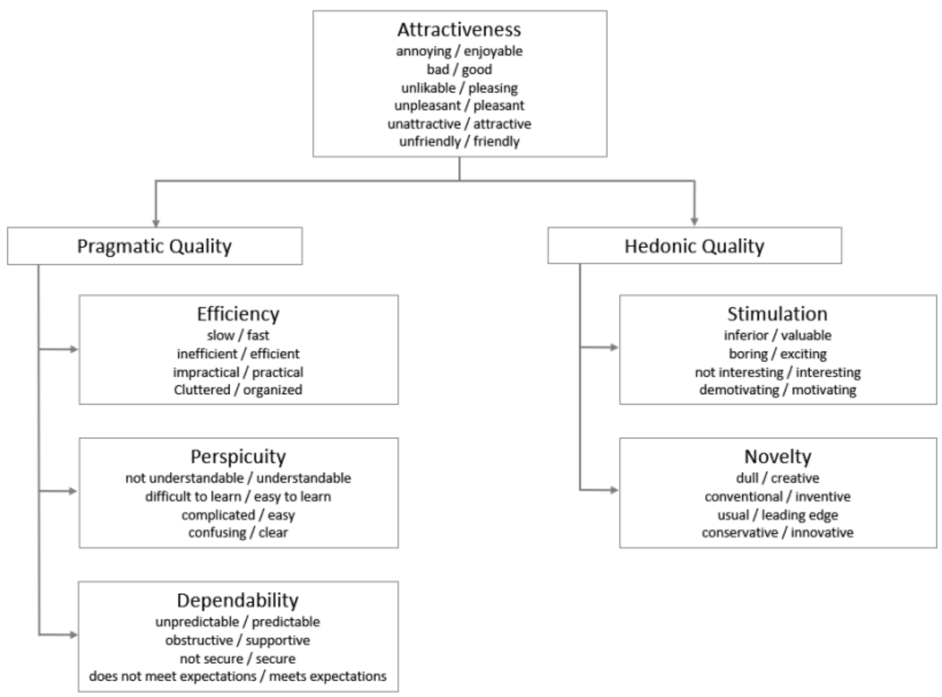


Figure 14 User Experience Questionnaire Structure

The questionnaire measures the participants' opinion on the Attractiveness, Perspicuity, Efficiency, Dependability, Stimulation and Novelty of the prototype. Attractiveness measures the general impression of the prototype on the users and how enjoyable they found the prototype. Perspicuity measures how easily the users learned to use the prototype. Efficiency measures how easily the users can achieve their goals while using the prototype. Dependability measures how well the prototype met the users' expectations in its effectiveness. Stimulation measures how excited or motivated the users are by the prototype and Novelty measures how innovative and creative the users found the prototype. Perspicuity, Efficiency and Dependability represent pragmatic values and Stimulation and Novelty represent hedonic values. Attractiveness represents a mixture of both these values. The questionnaire that was used in the user study is attached in **Appendix A**. Since this research aims to find the most effective visual feedback, the results for the efficiency category of the visual feedback types are the focus.

4.3 Procedure

Firstly, 24 randomly selected participants (beginners: 12, Intermediates: 9, Experts: 3) were collected for the evaluation. The participant read the information sheet and signed the consent form (**Appendix B and Appendix C**). A Pre-experiment questionnaire was done before the user test. The questionnaire collected general information about the users such as gender, weight, height, previous experience of weight training and history of injury. The pre-questionnaire is attached in **Appendix D**. Then, the participants watch a short video clip to learn how to perform the squat properly. After that, there was a brief introduction and demonstration of the experiment. Under the researcher's supervision, one correctly performed squat motion of each participant is recorded. Then the recorded data of the good squat motion will be used to calibrate the real-time feedback before the experiment. The participant then conducted a set of 10 squats with the only visual feedback being their mirror image (No added visual feedback). Then, the participant performed a set of 10 squats with each of the three visual feedback methods (Traffic light – A, Arrow – B, Avatar – C and All-in-One – D). The order of the visual feedback types between different participants was arranged according to a Latin square (A-B-C-D, B-C-D-A, D-A-B-C and C-D-A-B). Their performance was recorded by counting the number of good, moderate and poor squats they performed for each feedback method. A User Experience Questionnaire (UEQ) was distributed after completing 10 squats for each visual feedback type. At the end of the experiment, there was a general interview which collects users' feedback on the experiment and the prototypes.

Chapter 5
Result

5.1 Performance Measures

User performance was measured for each feedback type by counting how many good, moderate, and poor squats were performed. **Table 3** shows the total number of good, moderate and poor squats summed up across all participants for each visual feedback method. Then Chi-square analysis was done to see if there is a relationship between squat performance and visual feedback. As the calculated P-value was less than 0.05, there is a significant association between performance and visual feedback variables.

Table 3 Total Number of Performance for Overall Group

visual feedback / performance	No-visual feedback	Traffic	Arrow	Avatar	All-in-One	Total
Good	134	166	193	122	174	789
Moderate	83	61	41	102	64	351
Poor	23	13	6	16	2	60
Total	240	240	240	240	240	1200

Table 3 shows that participants achieved the highest number of good squats using Arrow, which was followed by All-in-One, Traffic, No-visual feedback and Avatar. Participants had moderate squats the most when they were using the Avatar followed by No-visual feedback, All-in-One, Traffic and Arrow. The participants performed the least number of poor squats in All-in-One, followed by Arrow, Traffic, and Avatar. When there was no visual feedback, the highest number of poor squats were observed. The percentage of good, moderate and poor squats for each feedback type are shown in **Figure 15**.

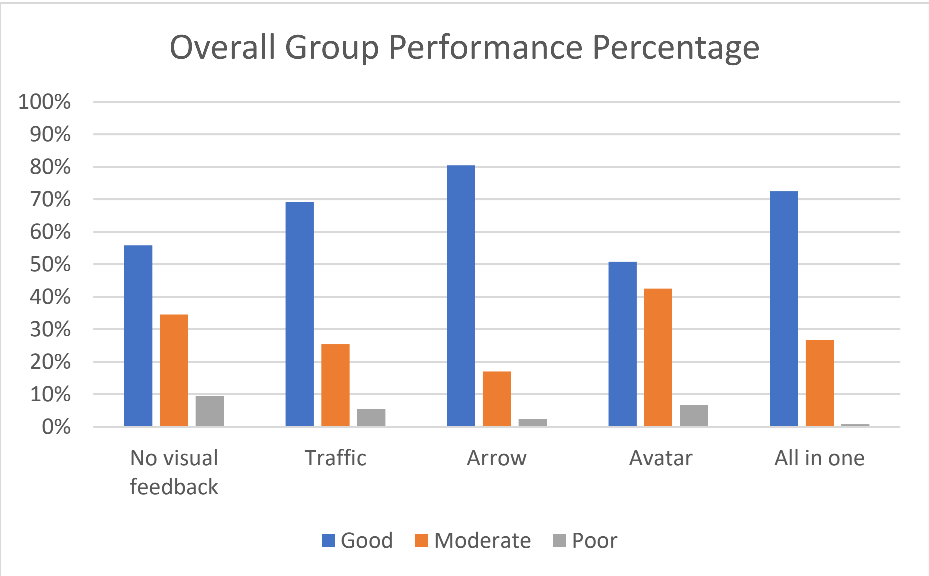


Figure 15 Performance Percentage for Overall Group

Then the participants' performance was analysed by dividing them into two groups: the beginner group and the advanced group (combined intermediates and experts). The total number of good, moderate and poor squats for each visual feedback type were summed up for all participants in the beginner and used to construct **Table 4**. Then Chi-square analysis was done for each group and both the resulting P-values were less than 0.05. Hence, there is a significant association between squat performance and visual feedback in both groups.

Table 4 Total Number of Performance for Beginners Group

visual feedback / performance	No-Visual Feedback	Traffic	Arrow	Avatar	All-in-One	Total
Good	81	91	106	81	104	463
Moderate	38	26	12	37	15	128
Poor	1	3	2	2	1	9
Total	120	120	120	120	120	600

In the beginner group, the result shows a very similar trend to the overall result. **Table 4** shows that participants achieved the most correct squats using the Arrow feedback followed by All-in-One and traffic. The participants achieved the same number of good squats using Avatar visual feedback and the no-visual feedback setting and they recorded the lowest number of good squats. Participants had moderate signs the most when they were given no visual feedback followed by Avatar, Traffic, All-in-One and Arrow. The participants performed the greatest number of wrong squats with the Traffic light feedback. Arrow and Avatar had the same number of wrong squats but were lesser compared to Traffic light feedback. Lastly, the no visual Feedback and All-in-One feedback case had the lowest number of wrong squats executed. The percentage of good, moderate and poor squats are shown in **Figure 16**.

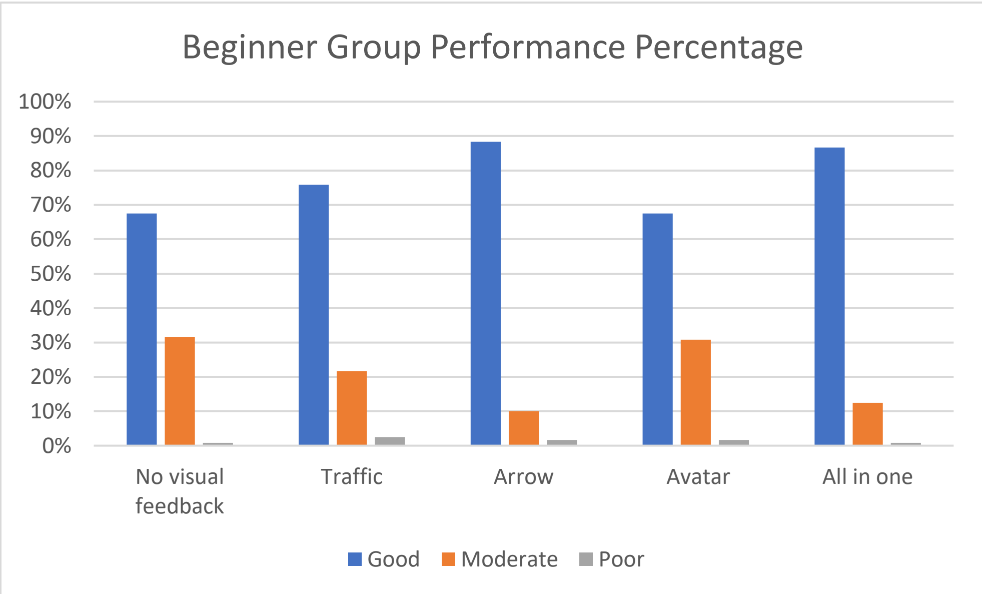


Figure 16 Performance Percentage for Beginner Group

Table 5 shows the performance of the squat for each visual feedback type for the advanced group.

Table 5 Total Number of Performance for Advanced Group

visual feedback / performance	No Visual Feedback	Traffic	Arrow	Avatar	All-in-One	Total
Good	53	75	87	41	70	326
Moderate	45	35	29	65	49	223
Poor	22	10	4	14	1	51
Total	120	120	120	120	120	600

The advanced group also achieved the greatest number of good squats with the Arrow feedback followed by Traffic, All-in-One, No visual Feedback and Avatar feedback. The Intermediate and expert participants had moderate signs the most when they were using Avatar visual feedback followed by All-in-One, no visual feedback, Traffic, and Arrow. The advanced group performed more poor squats compared to the beginner group. The no visual feedback had the greatest number of poor squats which was followed by Avatar, Traffic, Arrow and All-in-One feedback. The percentage of good, moderate and poor squats performed for each feedback type is shown **Figure 17**.

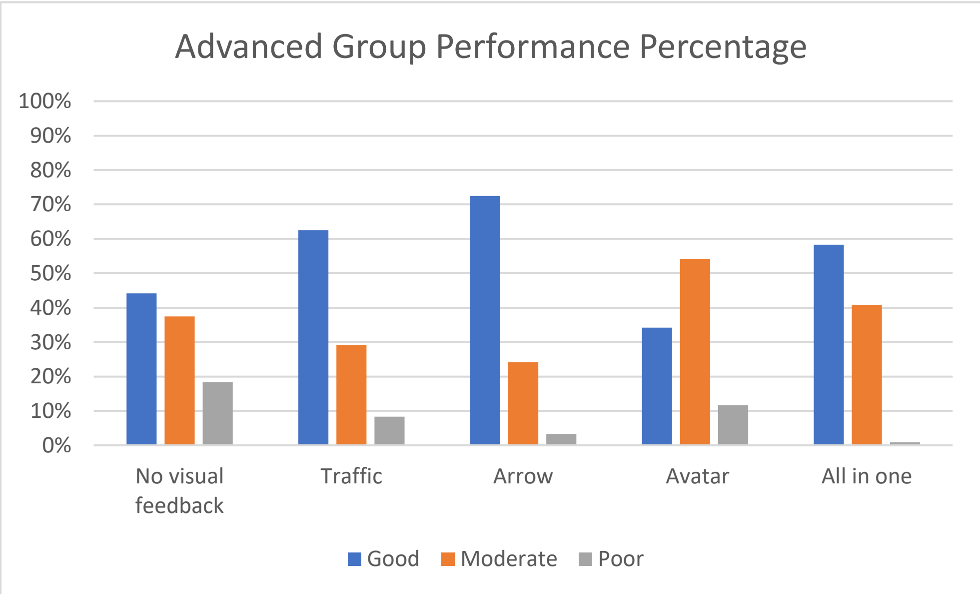
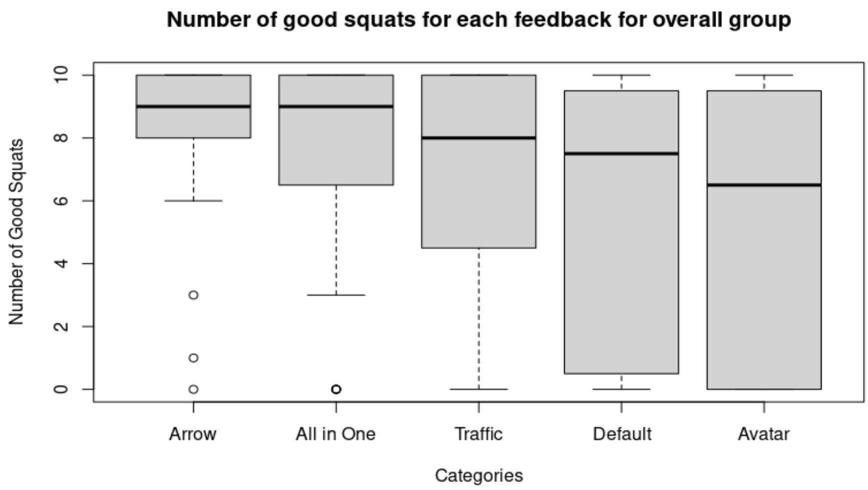


Figure 17 Performance Percentage for Advanced Group

Boxplots were generated for the overall group, beginner group, and advanced group to show the number of good, moderate, and poor squats performed by each participant. The boxplots show the distribution of the number of good squats, moderate or poor squats people performed instead of a single summed up value that was used in the previous analysis. From the distribution, it is possible to understand how variable the number of good squats was between participants. **Figure 18** shows the boxplots for the number of good and moderate squats performed by each participant for each visual feedback category.



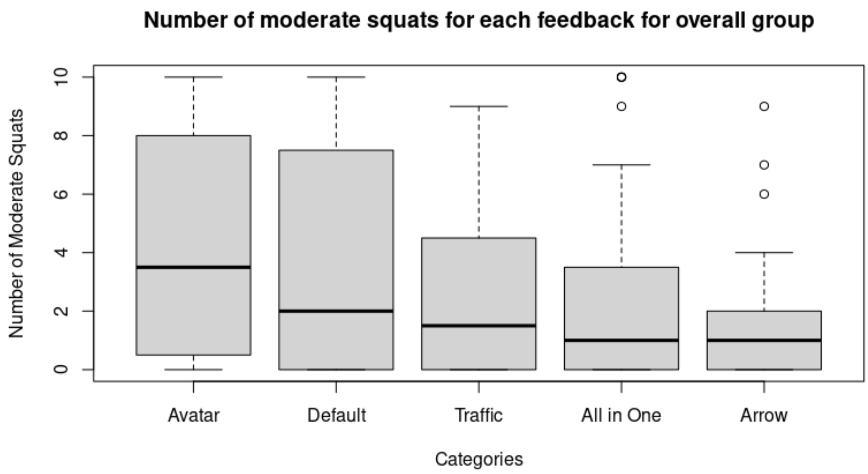
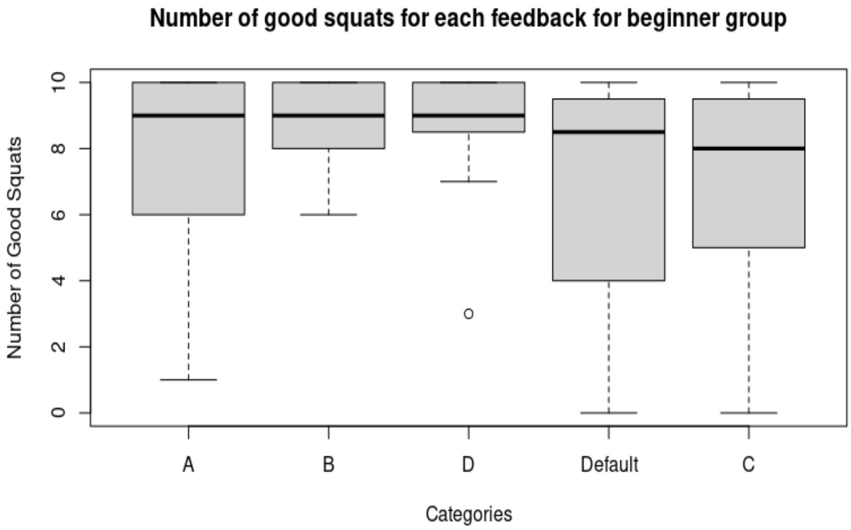


Figure 18 Boxplot for Overall Group Result of Good and Average Squats

The boxplots in **Figure 18** show that the median number of good squats were 9, 9, 8, 7.5 and 6.5 for Arrow, All-in-One, Traffic, Default and Avatar respectively. The median number of moderate squats were 3.5, 2, 1.5, 1, and 1 for Avatar, Default, Traffic, All-in-One and Arrow respectively. The number of poor squats observations were too small to be meaningfully represented by a boxplot so the boxplot for the number of poor squats was not included.

Box plots for the number of good and moderate squats performed by the beginner group was also created and is shown in **Figure 19**.



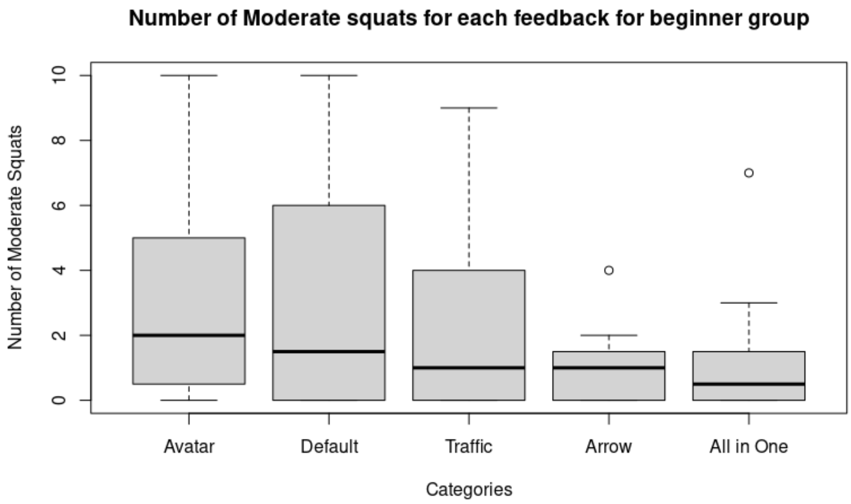


Figure 19 Boxplot for Beginner Group Result of Good and Average Squats

Figure 19 shows that the median number of good squats were 9, 9, 9, 8.5, and 8 for Traffic, Arrow, All-in-One, Default, and Avatar respectively. The median number of moderate squats were 2, 1.5, 1, 1, and 0.5 for Avatar, Default, Traffic, Arrow and All-in-One, respectively.

Figure 20 shows the boxplot for the advanced group.

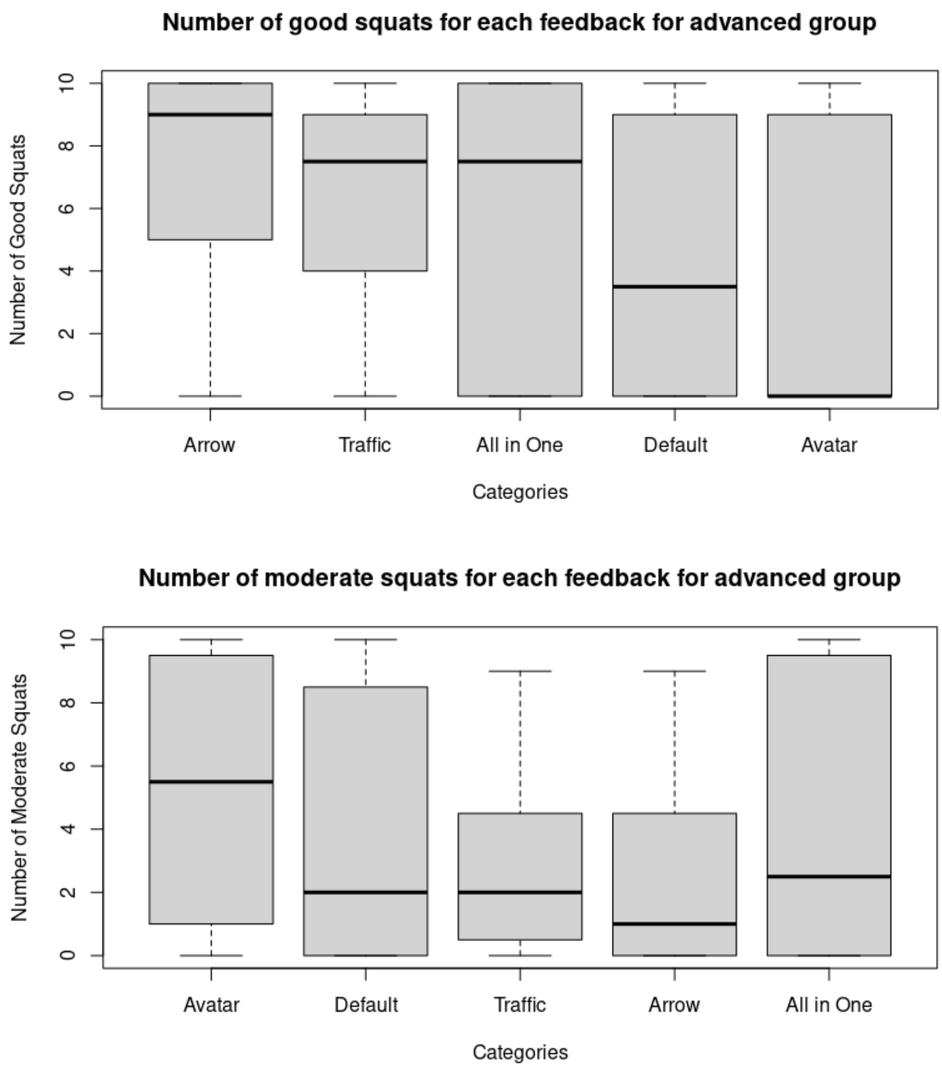


Figure 20 Boxplot for Advanced Group Result of Good and Average

Figure 20 shows that the median number of good squats were 9, 7.5, 7.5, 3.5, and 0 for Arrow, Traffic, All-in-One, Default and Avatar respectively. The median number of moderate squats were 5.5, 2.5, 2, 2, and 1 for Avatar, All-in-One, Traffic, Default and Arrow respectively.

To test whether there is a statistically significant difference between the number of good squats performed for the four visual feedback types, a one-way repeated measures ANOVA test was carried out. The test found a significant effect, F (4, 92) = 4.56, p = 0.002, partial $\eta 2/\eta_p 2$ = 0.162, which is commonly considered a large effect. Although this suggests that there is a significant difference in the mean number of good squats for the four visual feedback types, a post-hoc comparison must be performed to find which visual feedback types had a significant difference. The post hoc comparison results are shown in **Table 6**. In this table, the "Mean Difference" is calculated by subtracting the mean number of good squats of the right side's feedback type from the left side's feedback type.

Table 6 Post Hoc Comparison Summary Table

Post Hoc Comparisons - Number of good squats

Comparison							
Number of good squats		**Number of good squats**	**Mean Difference**	**SE**	**df**	**t**	**p_{tukey}**
Default	-	Traffic	-1.333	0.857	23.0	-1.56	0.539
	-	Arrow	-2.458	0.919	23.0	-2.68	0.089
	-	Avatar	0.500	0.828	23.0	0.60	0.973
	-	All-in-One	-1.667	0.711	23.0	-2.34	0.168
Traffic	-	Arrow	-1.125	0.646	23.0	-1.74	0.430
	-	Avatar	1.833	0.863	23.0	2.12	0.244
	-	All-in-One	-0.333	0.809	23.0	-0.41	0.994
Arrow	-	Avatar	2.958	0.871	23.0	3.40	0.019
	-	All-in-One	0.792	0.823	23.0	0.96	0.869
Avatar	-	All-in-One	-2.167	0.699	23.0	-3.10	0.037

The post-hoc comparison results show that the mean number of good squats for the Arrow feedback is higher than that of Avatar by 2.958 and this difference is significant as the p-value was less than 0.05. Also, the mean number of good squats in All-in-One is higher than that of Avatar by 2.167 and this difference is significant as the p-value is less than 0.05. This suggests that there is significant evidence that the users' mean number of good squats for the Arrow and All-in-One visual feedback was higher than that of the Avatar visual feedback.

5.2 Post Experiment Interview

In the post-experiment interview, the participants were asked to rank the visual feedback types according to their personal preferences. The summary for all participants of the overall group, beginner group and advanced group ranking is shown in **Table 7**, **Table 8**, and **Table 9**.

Table 7 Overall Group Preference Ranking Summary

	1st	2nd	3rd	4th
Traffic	8	7	4	5
Arrow	8	2	6	8
Avatar	3	8	8	5
All-in-One	5	7	6	6

Table 8 Beginner Group Preference Ranking Summary

	1st	2nd	3rd	4th
Traffic	2	4	2	4
Arrow	4	1	3	4
Avatar	1	5	3	3
All-in-One	5	2	4	1

Table 9 Advanced Group Preference Ranking Summary

	1st	2nd	3rd	4th
Traffic	6	3	2	1
Arrow	4	1	3	4
Avatar	2	3	5	2
All-in-One	0	5	2	5

Table 10 shows a summary of the feedback comments provided by the participants for each visual feedback method.

Table 10 Post Experiment Interview Summary

	Positive comments	Negative comments
Traffic	• Simple and easy • Flexibility in adjusting the pose • Clear when the users are doing correctly	• No specific information on how to fix the error • The colour was changing too fast
Arrow	• Clear feedback and intuitive • Simple to understand • Easy to understand • Flexibility in adjusting the pose • Provides specific feedback	• No visual feedback when you are doing correctly • Sudden changes • have to look down to see the arrow

Avatar	• good to see the whole body movement • Set up the pace for performing the squats • good to follow a well-calibrated movement • Easy to understand visually	• hard to match the speed • hard to distinguish yourself from the avatar • does not show if an error is made • No freedom to adjust the posture based on personal preference
All-in-One	• Most informative feedback • Provide useful information • Good to see the preventive and corrective methods at once • Could choose which one to follow	• Too much information • No freedom to adjust the posture based on personal preference • Complicated to understand

The participants also mentioned that they might prefer to have the following improvements added to the prototype:

- Sound effects, verbal, or text information
- Some participants wish they could see the side-view of their performance which might give them more information. Also, they wished that the visual feedback method can guide them about the appropriate depth of the squat, whether their back is straight, heels are still fixed on the group and other types of common errors.
- They wish that the Avatar and Traffic feedback methods or Arrow and Traffic feedback methods could be combined. They thought this combination will provide just enough information without being overwhelming.
- They suggested that having a clear outline of the avatar might be beneficial to allow them to distinguish between themselves and the avatar.
- They suggested that if the user makes mistakes, then pausing the avatar would be useful.

5.3 User Experience Questionnaire

For the qualitative measures in the user test, the independent variables are the 4 different visual feedback types: Traffic, Arrow, Avatar, and All-in-One. The dependent variables are the participants' responses to the UEQ questions. The UEQ contained 26 questions belonging to six general categories of Attractiveness, Perspicuity, Efficiency, Dependability, Novelty and Stimulation. As 26 questions are too many to meaningfully analyse the users' feedback for, a strategy for potentially grouping some of the results from the questions is required so that the feedback can be more easily analysed. A reliability analysis allows us to investigate if the response values of two or more variables are significantly correlated. If they are, those variables can be grouped, and their response values can be averaged to one value that represents that group. Thus, via a reliability analysis, a large number of variables can be condensed down to a more manageable amount, allowing us to obtain more reliable and stable insights. The significance of a relationship between variables is established by the value of Cronbach's alpha. As there are five broad categories that the 26 questions fall under in the UEQ, reliability analysis for the questions in each category was done to see if the responses for the questions in each category are significantly related. The responses were arranged so that higher values represent a more positive score. The results for the Internal reliability analysis of Attractiveness, Perspicuity, Efficiency, Dependability, Novelty and Stimulation were above the significant level as the Cronbach's alpha values were 0.90, 0.86, 0.72, 0.86, 0.88, and 0.85, respectively. Thus, the response values for each question within each category were averaged and used to represent that category. These averaged values for the UEQ feedback categories across all participants for each visual feedback type are represented by a bar graph in **Figure 21**.

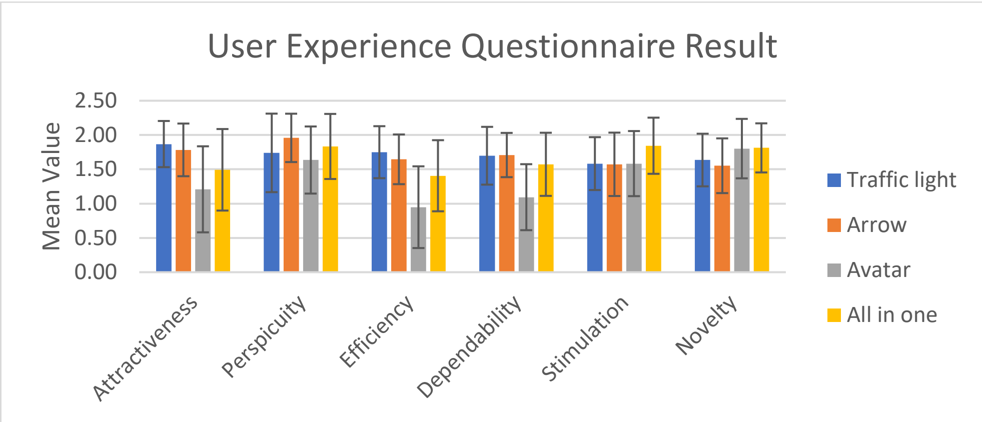


Figure 21 User Experience Questionnaire

The previous reliability analysis allows us to get a mean value for each UEQ category for each visual feedback type. However, to compare the visual feedback types' UEQ results, an analysis of whether the differences in mean category values between the visual feedback types are statistically significant must be performed. To do this analysis, a one-way repeated measures ANOVA (analysis of variance) test was performed. The repeated measures used by ANOVA were the mean response values given by a participant for each UEQ category repeatedly measured for the various visual feedback types (shown in **Appendix E**). This test finds the significance of the difference in the means of the visual feedback types within each UEQ category.

The p-values of mean differences between the visual feedback types for the Attractiveness, Perspicuity, Novelty and Stimulation categories were bigger than 0.05 which means that there is no significant difference between the visual feedback methods for these categories (shown in **Table 11**).

Table 11 Summary of ANOVA test

Within Subjects Effects

	Sum of Squares	df	Mean Square	F	p	η^2_p
Attractiveness	6.47	3	2.158	2.49	0.068	0.098
Perspicuity	1.36	3	0.453	0.348	0.791	0.015
Efficiency	9.16	3	3.054	3.82	0.014	0.143
Dependability	6.04	3	2.013	3.28	0.026	0.125
Stimulation	1.26	3	0.418	0.630	0.598	0.027
Novelty	1.18	3	0.393	0.985	0.405	0.041

However, a significant effect was found for the Efficiency category, $F(3, 69) = 3.82$, $p = .014$, partial η^2/ $\eta^2_p = .143$, which is commonly considered a large effect. A significant effect was also found for the Dependability category, $F(3, 69) = 3.28$, $p = .026$, partial η^2/ $\eta^2_p = .125$, which is commonly considered a medium effect. This means that some of the visual feedback types had a significant difference in means for the Efficiency and Dependability categories.

To find out which visual feedback types' means have a significant difference for the efficiency and dependability categories, the post hoc test was done and shown in **Table 12** and **Table 13**. In these tables, the "Mean Difference" is calculated by subtracting the mean value of the response of the right side's feedback type from the left side's feedback type.

Table 12 Summary of Post Hoc Comparisons for Efficiency

Post Hoc Comparisons – **Efficiency**

Comparison							
Efficiency		**Efficiency**	**Mean Difference**	**SE**	**df**	**t**	**p_{tukey}**
Traffic	-	Arrow	0.104	0.228	23.0	0.458	0.967
	-	Avatar	0.802	0.225	23.0	3.569	0.008
	-	All-in-One	0.344	0.239	23.0	1.437	0.490
Arrow	-	Avatar	0.698	0.290	23.0	2.405	0.104
	-	All-in-One	0.240	0.320	23.0	0.749	0.876
Avatar	-	All-in-One	-0.458	0.231	23.0	-1.984	0.223

Table 13 Summary of Post Hoc Comparisons for Dependability

Post Hoc Comparisons – **Dependability**

Comparison							
Dependability		**Dependability**	**Mean Difference**	**SE**	**df**	**t**	**p_{tukey}**
Traffic	·	Arrow	-0.010	0.236	23.0	-0.044	1.000
	·	Avatar	0.604	0.207	23.0	2.921	0.036
	·	All-in-One	0.125	0.260	23.0	0.480	0.963
Arrow	·	Avatar	0.615	0.237	23.0	2.594	0.072
	·	All-in-One	0.135	0.244	23.0	0.554	0.945
Avatar	·	All-in-One	-0.479	0.156	23.0	-3.080	0.025

The summary of the post hoc test shows that the mean response for the Traffic feedback is higher than Avatar for the Efficiency category and has a significant difference (p-value < 0.05). This indicates that there is significant evidence that the participants considered the efficiency of Traffic to be higher than that of Avatar. For the dependability post hoc test, Traffic and All-in-One have a higher mean value than Avatar and there is a significant difference (p-value < 0.05). This indicates that there is significant evidence that users found the Traffic and All-in-One feedback to be easier to understand than Avatar. These statistical significance results are in line with the feedback given by the participants in the post-experiment Interview.

Chapter 6
Discussion

A prototype using Kinect v2 was built to provide AR-based real-time visual feedback during a squat. 24 (20 males and 4 females) participants were collected for the user study and the measurements were done along three dimensions: performance, post-experiment interview, and UEQ. In the performance measurement, the number of good, moderate and poor squat forms were counted while the user is given different types of visual feedback which were Traffic, Arrow, Avatar, and All-in-One. Also, users' performance was measured without any visual feedback given for comparison.

6.1 Performance Measurements

6.1.1 Barplot and Table Analysis

Overall Group - The overall number of good, moderate and poor squats were then tallied up for each visual feedback type and are shown in **Table 3** and **Figure 15**. This table shows that generally, the participants were able to perform a higher number of good squats with visual feedback. Especially, the users' number of good squats improved the most using Arrow visual feedback, followed by All-in-One and Traffic. The Avatar visual feedback was not seen to show a useful improvement since the participants achieved a smaller number of good squats when Avatar visual feedback was given compared to when no visual feedback was given. However, the number of poor squats performed during the Avatar visual feedback was still less than the number of poor squats performed when no visual feedback so there is a moderate improvement in terms of reduction of errors. Then the participants' data was split into two different groups according to their level of expertise: the beginner group and the advanced group (intermediate and experts together). This was done to investigate how the participants' level of expertise affects their performance for the different visual feedback types.

Beginner Group - **Table 4** and **Figure 16** show a tally-up table and a bar plot of the percentage of the number of good, moderate, and poor squats performed by the beginner group for each visual feedback type, respectively. The beginner group's performance showed the same trend as the overall result. They performed the greatest number of good squats with Arrow visual feedback, followed by All-in-One, Traffic, and Avatar. However, the percentage of good squats performed in the beginner group increased for the All-in-One feedback type compared to the overall group result. All-in-One provides the largest amount of visual information as this feedback type is an amalgamation of all other feedback types. Thus, it could have been more helpful for the beginner group as they do not have much prior experience and more information could give them more guidance to be able to perform good squats. In the beginner group, Avatar is the only visual feedback type that reduces the performance of the squat compared to the no visual feedback setting. This is because the low transparency overlapping avatar was too similar to their image and confused them while performing the squat.

Advanced Group - **Table 5** and **Figure 17** show a tally-up table and a bar plot of the percentage of the number of good, moderate, and poor squats performed by the advanced group for each visual feedback type, respectively. The advanced group also achieved the highest number of good squats with the Arrow visual feedback, followed by Traffic, All-in-One, and Avatar. So, for the advanced group, the Traffic feedback was the second-best instead of All-in-One, which is the opposite order compared to the beginner group. This could be because as the advanced group already have experience in performing squats, they do not benefit from a large amount of information from a feedback method like All-in-One. It could have instead interrupted their understanding of performing squats correctly due to a large amount of information. Similar to All-in-One, the Avatar feedback guides the participants to follow the movement trajectory of the previously recorded squat exactly, which could be over constraining their movement. As this group already has sufficient knowledge and experience to distinguish how to fix mistakes during the squats, just simple and intuitive indications such as colour or arrow pointers were more efficient for them. An interesting result was that in general, the advanced group performed a lesser number of good squats and an increased number of poor and moderate squats than the beginner group across all feedback types, as shown in **Figure 16** and **Figure 17**. This could be because due to their previous experience in performing squats, they are more likely to perform adjustments to their movements according to personal judgement, which could lead to deviation from the previously performed good squat used for calibration. However, the beginner group could have adhered more strictly to the provided visual feedback and not let personal judgement affect their movements.

6.1.2 Boxplot Analysis

Although the previous analysis provides information about the ranking of the visual feedback methods based on the number of good, moderate, or poor squats performed, it does not provide insights into the variability of the squat performance between the participants. Hence, boxplots for the number of good and moderate squats performed by each participant against the feedback category were constructed. This was done for all participants and the beginner and advanced groups. For each group, the descending order of the median number of good and moderate squats remains the same generally as the previously determined order for the tallied-up percentage of good and moderate squats. In general, across all groups, the feedback modes with a higher median number of good squats had a lesser spread. Conversely, feedback modes with a higher median number of moderate squats had a higher spread. This suggests that feedback modes that lead to better squat performance are also more consistent between participants.

For the group of all participants, the arrow feedback type had the least spread in the number of good and moderate squats and the highest and lowest median value, respectively. This suggests that overall, the participants had a better and more consistent performance with arrow feedback. This was also true for the advanced group. For the beginners' group, Traffic, Arrow and All-in-One had almost the same medians for the number of good and moderate squats, being highest for the good squats and lowest for the moderate squats. However, All-in-one had the lowest spread for the number of good squats and moderate squats performed by the beginner participants. This suggests that beginner participants had the best and most consistent performance with All-in-One feedback. These results are in line with the fact that experienced users benefit from the more intuitive type of feedback such as Arrow, which does not contain an overwhelming amount of information. However, beginner participants benefit from feedback types that contain the maximal amount of information to account for their lack of knowledge in performing squats correctly.

For the group of all participants, Arrow and All-in-One had the highest median good squats, and Avatar had the lowest. The exact opposite order was seen for the median number of moderate squats. This suggests that Arrow and All-in-One generally had the best performance, whereas Avatar had the lowest performance. For the advanced group, Arrow had the highest median number of good squats, and Avatar had the lowest median number of good squats. The exact opposite ordering was seen for the median number of moderate squats. This suggests that Arrow was the best performing visual feedback and Avatar was the worst-performing mode. Traffic, Arrow and All-in-One all had the highest median number of good squats, and Avatar was the lowest for the beginner group. All-in-One recorded the lowest value for the median number of moderate squats, and Avatar recorded the highest. All-in-One also had the least spread for both the number of good and moderate squats.

6.2 Post-Experiment Interview

After finishing the experiment, all users were asked to rank the visual feedback modes according to their personal preferences. Overall, beginner and advanced groups show different preferences. First, the overall group result in **Table 8** shows that Traffic and Arrow were selected as the most preferred modes. Traffic was chosen the least frequently for the worst visual feedback. However, Arrow was also frequently selected for the most un-preferred visual feedback. The preference for Arrow was very polarized between the beginner and advanced groups as well. This tells that the Arrow feedback can be interpreted in diverging ways based on the user's preference. There was a clear difference in preference for the Traffic feedback between the advanced and the beginner groups. The advanced group most frequently ranked Traffic as the most preferred feedback, whereas the beginner group most commonly ranked it as the least preferred feedback. Another difference in preference between the groups was noticed for the All-in-One feedback. The advanced group most frequently chose it as the least preferred mode whereas the beginners chose it as the most preferred mode frequently. This could be because the advanced group might prefer more simple and intuitive feedback such as Traffic and Arrow that moderately augments their already developed experience in performing squats. However, the beginner group preferred to have visual feedback that contains more detailed information to fix their pose, such as All-in-One.

6.3 User Experience Questionnaire

A UEQ was also given to the users at the end of each visual feedback so that they could score it on various aspects such as Attractiveness, Perspicuity, Efficiency, Dependability, Stimulation and Novelty. Because the visual feedback methods aim to improve the effectiveness of squat performance, the efficiency category is important as it gauges the users' perception of the effectiveness of the feedback modes. The feedback modes in descending order of mean efficiency scores given by the users were Traffic light, Arrow, All-in-One and Avatar. By performing an ANOVA test, a significant difference between the scores of different visual feedback types was found for the Efficiency and Dependability categories. A post-hoc comparison was made to find that the Traffic feedback's mean value of the efficiency score was significantly higher than Avatar, and the dependability score means of Traffic and All-in-One feedback was significantly higher than Avatar. This result is in line with the low favourability demonstrated for Avatar in the user preference ranking in contrast to the Traffic and All-in-One feedback modes.

6.4 Limitations

The limitations of this research were that since this prototype was focusing on fixing knee-collapsing scenarios, it was hard to detect when there were other mistakes such as butt wink, heels off the ground, rounded back or too shallow squat. The skeleton tracking by Kinect v2 on the knee joints was unstable and faced minor glitching, which could have decreased the effectiveness of the visual feedback methods that relied on the tracking information such as Traffic, Arrow, and All-in-One. For future work, the skeleton structure could be tracked more precisely and accurately if Azure Kinect was used. For the UEQ results, a significant difference in the mean scores between the feedback modes for the other categories such as attractiveness, perspicuity, stimulation, and novelty cannot be found. It is not likely that all four feedback modes do not have differences in attributes relating to these categories. Thus, it is possible that an insignificant difference could have been found because the sample size is not large enough. This could be improved by having more participants in a future experiment.

Chapter 7
Conclusion and Future Work

This research aims to answer the question, “Can visual feedback using AR technology reduce mistakes during squat training?”. AR feedback was used to provide visual feedback to enhance the execution of squats by detecting the knee collapse error. Kinect v2 was used for motion capturing and generating a skeleton model of the user to obtain the coordinates of the user’s joints. Then Unity was used to predict errors by analysing the joint data. After identifying the errors, Unity was also used to implement the user interface that provides different types of visual feedback to improve a user’s squat performance: Traffic, Arrow, Avatar, and All-in-One. The Traffic feedback involves using green, yellow, and red colours to indicate the correctness of the squat motion in terms of the level of knee collapse occurring. The Arrow visual feedback shows arrow pointers beside the user’s knees when the knee starts to collapse inwards. The more the knee collapses, the bigger the arrows get. For the Avatar visual feedback method, the best squat form of the user is recorded initially for calibration. Then the recorded video is translucently overlapped on top of the user’s mirror image so the users can follow their correctly performed squat motion.

Finally, All-in-One is a combination of all visual feedback types. Twenty-four participants were gathered (four females) who have different levels of expertise in weightlifting (beginner, intermediate and expert). Then they performed ten squats with each visual feedback. Since the perfect squat form can differ according to each person’s physiology, the machine was initially calibrated. The errors in future squats were detected by the degree of deviation from their correct squat form. The level of deviation was utilised to provide visual feedback and evaluate the correctness of their squat. A correct squat was recorded as “good”, a slight deviation from the correct squat was recorded as “moderate”, and a large deviation was recorded as “poor”. Also, a UEQ was done after the user completed ten squats for each visual feedback. Then the post-experiment interview was done to collect personal preferences and further comments on the prototype.

The overall performance results show improved their squat performance the best using Arrow visual feedback, followed by All-in-One, Traffic and Avatar. Then further analysis was done by dividing the participants into two groups: the beginner and advanced (combined intermediates and experts). For the beginner group, they performed the best using Arrow, followed by All-in-One, Traffic and Avatar. However, for the advanced group, results show that they performed better in the order of Arrow, Traffic, All-in-One and Avatar. This difference between the groups could emerge because beginners could benefit from the large amount of information provided by All-in-One visual feedback due to their lack of experience more than the experienced participants. However, for the advanced group, All-in-

One could have provided too much unnecessary information for them, and it was interrupting their judgement and squat performance. Therefore, the advanced group performed better with simple and intuitive visual feedback methods such as Arrow and Traffic. The participants' personal preferences were similar but had minor differences from the performance results. Overall, participants preferred Traffic over Avatar. This could be because the Traffic visual feedback was easy to understand for most participants.

In contrast, the Avatar was confusing due to the participants not being able to distinguish their own image with the translucent avatar overlay. The preference of the beginner group was ranked in the order of All-in-One, Arrow, Traffic and Avatar, and the preference rank in the advanced group was Traffic, Arrow, Avatar and All-in-One. The UEQ results also show users' perception of the efficiency of visual feedback modes. The order is Traffic, Arrow, All-in-One, and Avatar, which follows the trend in preference result. There are some suggestions from the participants. Firstly, instead of mixing all three visual feedbacks, maybe mixing two visual feedbacks would be sufficient to get the desired information, such as Arrow + Traffic or Avatar + Traffic. Also, many participants wanted to do squats at their own pace rather than the fixed pace of the avatar. Hence, they wished that the avatar adapted to their pace. Finally, they also mentioned that other types of feedback, such as sound effects or text, could better guide them while doing squats.

For future work, incorporating side-view feedback can provide additional useful information for the user since this could give feedback on the position of their back, hip and ankles, which are the parts where many weightlifters make mistakes. Another possible improvement could involve using machine learning to detect errors instead of user-based calibration done in this research. User-based calibration requires manually constructing methods using the joint positions to detect errors. At the same time, machine learning-based methods can automatically learn complex relationships between the joint data and errors to detect errors more powerfully in squat performance. The prototype developed could also be extended for applications in other types of strength exercises such as the deadlift, bench press or shoulder press. Moreover, this can also be applied to sports where repetitive and correct execution of movements is required, such as golf, basketball, and baseball.

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Appendix

Appendix A

UEQ Questions

Please make your evaluation now.

For the assessment of the product, please fill out the following questionnaire. The questionnaire consists of pairs of contrasting attributes that may apply to the product. The circles between the attributes represent gradations between the opposites. You can express your agreement with the attributes by ticking the circle that most closely reflects your impression.

Example:

attractive	○	⊗	○	○	○	○	○	unattractive

This response would mean that you rate the application as more attractive than unattractive.

Please decide spontaneously. Don't think too long about your decision to make sure that you convey your original impression.

Sometimes you may not be completely sure about your agreement with a particular attribute or you may find that the attribute does not apply completely to the particular product. Nevertheless, please tick a circle in every line.

It is your personal opinion that counts. Please remember: there is no wrong or right answer!

Please assess the product now by ticking one circle per line.

	1	2	3	4	5	6	7		
annoying	○	○	○	○	○	○	○	enjoyable	1
not understandable	○	○	○	○	○	○	○	understandable	2
creative	○	○	○	○	○	○	○	dull	3
easy to learn	○	○	○	○	○	○	○	difficult to learn	4
valuable	○	○	○	○	○	○	○	inferior	5
boring	○	○	○	○	○	○	○	exciting	6
not interesting	○	○	○	○	○	○	○	interesting	7
unpredictable	○	○	○	○	○	○	○	predictable	8
fast	○	○	○	○	○	○	○	slow	9
inventive	○	○	○	○	○	○	○	conventional	10
obstructive	○	○	○	○	○	○	○	supportive	11
good	○	○	○	○	○	○	○	bad	12
complicated	○	○	○	○	○	○	○	easy	13
unlikable	○	○	○	○	○	○	○	pleasing	14
usual	○	○	○	○	○	○	○	leading edge	15
unpleasant	○	○	○	○	○	○	○	pleasant	16
secure	○	○	○	○	○	○	○	not secure	17
motivating	○	○	○	○	○	○	○	demotivating	18
meets expectations	○	○	○	○	○	○	○	does not meet expectations	19
inefficient	○	○	○	○	○	○	○	efficient	20
clear	○	○	○	○	○	○	○	confusing	21
impractical	○	○	○	○	○	○	○	practical	22
organized	○	○	○	○	○	○	○	cluttered	23
attractive	○	○	○	○	○	○	○	unattractive	24
friendly	○	○	○	○	○	○	○	unfriendly	25
conservative	○	○	○	○	○	○	○	innovative	26

Appendix B

Information Sheet

Department: HIT/Human Interface Technology
Telephone: +64 3 369-0219
Email: sch237@uclive.ac.nz
06/11/2021
HEC Ref:

Optimising visual feedback on squat motion error detection
Information Sheet for participants

We are a research group at the HIT Lab, NZ. We are developing optimising visual feedback on squat motion error detection.

You have been approached to take part in this study to support the research on developing the most effective visual feedback system for strength training. I have located your contact details in an Excel file.

If you choose to take part in this study, you will be asked to provide some general personal information. Next, the procedures of the experiment will be explained. The experiment will involve performing a few sets of squat exercises with a monitor that provides visual feedback on the performance of squat motions. The performance of your squats will be measured. For each visual feedback type, you will be asked to respond to a questionnaire. At the end of the experiment, you will be asked a few questions about your experience and the interview will be audio-recorded. Overall, the experiment will take approximately 45-60 minutes

As a result of participating in the experiment, there are risks of tired legs. The experiment will be stopped immediately when the participant feels tired. Also, a chair is prepared to relieve leg fatigue after the experiment if it is required.

Participation is voluntary and you have the right to withdraw at any stage without penalty. You may ask for your raw data to be returned to you or destroyed at any point. If you withdraw, I will remove information relating to you. However, once the analysis of raw data starts in February 2022, it will become increasingly difficult to remove the influence of your data on the results.

The results of the project may be published, but you may be assured of the complete confidentiality of data gathered in this investigation: your identity will not be made public without your prior consent. To ensure anonymity and confidentiality, all the data is stored securely and only the researchers mentioned in the consent sheet will have access to it. However, we might also share parts of the raw or analysed data with other researchers if there is a need to do so. The data will be kept securely stored for a minimum period of 5 years on storage systems within the University of Canterbury, and securely destroyed after that.

Please indicate to the researcher on the consent form if you would like to receive a copy of the summary of the results of the project.

The project is being carried out by Leon Chun under the supervision of Stephan Lukosch and Thammathip Piumsomboon, who can be contacted at sch237@uclive.ac.nz, stephan.lukosch@canterbury.ac.nz and tham.piumsomboon@canterbury.ac.nz respectively. He will be pleased to discuss any concerns you may have about participation in the project.

This project has been reviewed and approved by the University of Canterbury Human Ethics Committee, and participants should address any complaints to The Chair, Human Ethics Committee, University of Canterbury, Private Bag 4800, Christchurch (human-ethics@canterbury.ac.nz).
Leon Chun

Please review the consent form. If you agree to participate in the study, please sign, scan/take a photo of, and return the consent form to the researcher through email or hand it back in person on your preference. Otherwise, you can also complete the consent form and return it before commencing the experiment

Leon Chun

Appendix C
Consent Form

UNIVERSITY OF CANTERBURY
Te Whare Wānanga o Waitaha
CHRISTCHURCH NEW ZEALAND

Department: Human Interface Technology Laboratory New Zealand
Telephone: +64 3 369-0219
Email: sch237@uclive.ac.nz

Optimising visual feedback on squat motion error detection
Consent Form for Participants

Include a statement regarding each of the following:

- ☐ I have been given a full explanation of this project and have had the opportunity to ask questions.
- ☐ I understand what is required of me if I agree to take part in the research.
- ☐ I understand that participation is voluntary and I may withdraw at any time without penalty. Withdrawal of participation will also include the withdrawal of any information I have provided should this remain practically achievable.
- ☐ I understand that any information or opinions I provide will be kept confidential to the researcher Leon Chun, Stephan Lukosch and Thammathip Piumsomboon and that any published or reported results will not identify the participants.
- ☐ I understand that all data collected for the study will be kept in locked and secure facilities and/or in password-protected electronic form and will be destroyed on completion of the research project.
- ☐ I understand that the raw data or analysed data could be shared with other researchers for related development, teaching or research.
- ☐ I do not have any historical joint injury or surgery.
- ☐ I have not consumed alcohol during the past 6 hours.
- ☐ I understand the risks associated with taking part and how they will be managed.
- ☐ I understand that I can contact Professor Stephan Lukosch (stephan.lukosch@canterbury.ac.nz, +64 3 369 1308) for further information. If I have any complaints, I can contact the Chair of the University of Canterbury Human Ethics Committee, Private Bag 4800, Christchurch (human-ethics@canterbury.ac.nz)
- ☐ If I would like a summary of the results of the project, the researcher will send the summaries of the outcomes of this measurement to my email address that is provided in this form.
- ☐ By signing below, I agree to participate in this research project.

Name:____________________________Signed:__________________________Date:________________

Email address *(for a report of findings, if applicable)*:____

Leon Chun

Appendix D
Pre-questionnaire

Participant number

Pre-Experiment Questionnaire

1. Name:
2. Gender
   - Male
   - Female
   - Please specify ______________________________
   - Don't want to specify
3. Age:
4. Weight: (kg/lb) Height: (cm/ft)
5. Do you have joint pain in general or injury or surgery history?
   - No
   - Yes, if so, where and what kind of injury or surgery was it?

____

____

____

6. Do you have experience in squatting?
   - No
   - Yes, if so, how would you describe your expertise? ______________

     Beginner – Never get trained or taught before
     Intermediate – Been taught or trained but not stable or make mistakes
     expert – comfortable doing squatting alone without making mistakes

Thank you!

Appendix E

UEQ average values

	Average values																							
	Traffic						Arrow						Avatar						All in One					
Participant	Attractiveness	Perspicuity	Efficiency	Dependability	Stimulation	Novelty	Attractiveness	Perspicuity	Efficiency	Dependability	Stimulation	Novelty	Attractiveness	Perspicuity	Efficiency	Dependability	Stimulation	Novelty	Attractiveness	Perspicuity	Efficiency	Dependability	Stimulation	Novelty
1	1.50	2.75	1.25	1.25	1.00	1.00	1.17	2.25	1.00	1.50	2.00	2.00	0.17	1.00	0.75	0.25	0.75	1.25	1.33	1.00	1.00	1.50	1.50	1.25
2	2.00	2.00	1.75	2.75	1.75	1.25	2.50	2.50	1.50	3.00	2.75	1.50	3.00	3.00	1.75	2.75	3.00	1.75	2.83	3.00	2.25	2.75	2.50	2.25
3	2.67	2.75	2.00	1.75	2.50	2.75	0.50	0.25	2.00	1.75	1.75	2.25	-1.17	1.50	0.25	0.50	1.00	3.00	-2.33	-0.25	-0.25	0.50	2.25	3.00
4	1.50	1.50	1.25	1.25	0.25	0.75	2.00	2.75	2.75	1.25	2.25	2.50	-1.67	0.50	-1.50	-1.00	-1.25	-1.25	-0.33	0.75	-0.75	-0.75	0.75	0.50
5	1.83	2.25	1.25	2.25	2.00	2.00	0.80	0.75	-0.25	1.25	0.75	0.75	-0.83	-2.00	-2.50	0.00	1.50	1.50	2.17	2.00	1.25	2.00	3.00	2.00
6	3.00	3.00	3.00	3.00	2.75	3.00	2.50	0.50	1.50	1.00	-0.25	1.75	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
7	1.33	1.75	1.50	1.50	1.00	1.00	0.33	1.00	0.50	0.00	-0.50	0.00	1.17	1.25	1.00	1.25	1.00	1.25	1.67	1.75	1.25	1.50	1.75	1.75
8	1.83	3.00	1.75	2.00	1.00	-0.50	2.33	3.00	2.00	2.25	2.00	1.00	0.67	0.50	0.25	-0.25	1.75	2.00	0.17	-0.25	-0.50	-0.75	0.75	1.75
9	2.50	2.50	2.00	2.00	2.50	2.25	2.17	2.50	1.75	2.00	2.00	2.00	2.50	2.75	2.00	2.50	2.50	2.75	2.83	3.00	3.00	2.75	2.50	2.50
10	1.33	1.50	1.25	1.25	1.25	1.25	1.67	2.75	1.75	2.00	1.75	0.75	-1.00	1.50	-0.50	0.25	-0.50	0.75	-2.50	-1.00	-1.75	0.00	-1.50	0.00
11	1.00	0.00	0.50	1.00	0.75	0.25	0.17	1.50	0.50	0.25	-0.25	-0.50	0.33	1.75	0.00	0.00	1.00	0.75	1.33	0.50	0.75	-0.25	1.25	0.00
12	1.67	2.75	1.75	1.25	1.00	1.75	1.50	1.00	1.25	2.00	0.75	0.50	0.33	2.00	1.00	0.00	0.00	1.00	0.83	2.00	1.00	0.25	1.00	1.50
13	1.17	0.50	1.00	1.00	1.75	3.00	2.67	2.50	2.25	2.50	2.50	1.50	1.83	3.00	1.75	1.75	1.75	1.25	2.83	2.00	2.75	2.50	2.50	1.50
14	3.00	3.00	2.75	2.75	2.50	2.75	1.50	1.00	0.75	2.00	0.75	0.75	2.50	1.00	2.25	2.00	2.50	2.50	2.50	3.00	2.50	2.75	1.75	2.50
15	2.67	3.00	2.75	2.25	1.75	1.75	2.67	3.00	2.75	2.50	3.00	2.75	2.67	2.25	2.00	2.50	2.75	3.00	2.67	3.00	3.00	2.50	2.75	2.25
16	0.17	-2.75	-0.25	-1.25	0.25	1.50	2.50	2.50	2.25	2.00	1.75	2.00	-0.17	0.25	-1.75	-1.00	1.50	2.75	1.00	1.75	0.50	1.75	1.50	2.50
17	2.00	2.75	2.50	2.50	1.75	1.50	1.83	2.25	2.25	2.00	2.00	1.75	3.00	2.75	2.25	2.25	2.75	2.75	2.17	3.00	2.25	2.25	2.25	1.75
18	1.50	2.25	1.75	1.25	1.00	0.25	-0.50	0.75	-0.25	0.00	-1.00	0.00	-1.00	0.00	-0.50	0.25	-0.25	0.00	1.17	3.00	2.25	1.75	0.75	0.25
19	0.00	-1.25	0.00	-0.50	-0.75	1.00	1.83	2.00	1.50	1.25	1.25	1.00	2.17	2.25	1.00	1.00	1.75	1.25	2.17	2.00	0.75	1.75	2.00	1.50
20	2.67	2.50	3.00	2.50	2.75	2.75	3.00	1.75	2.50	2.25	2.50	3.00	3.00	2.75	3.00	2.25	3.00	2.75	2.33	2.50	2.50	2.00	3.00	2.75
21	3.00	1.50	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	2.50	3.00	2.25	2.50	2.50	2.75	2.83	3.00	2.25	3.00	3.00	3.00
22	2.33	2.25	2.75	2.00	2.00	2.25	1.67	2.25	1.75	1.75	1.75	2.00	2.67	2.50	1.50	1.25	2.50	2.75	1.67	2.25	1.00	1.75	2.00	2.00
23	2.83	1.25	2.75	3.00	3.00	1.50	3.00	2.75	2.75	1.50	3.00	3.00	1.83	1.25	2.50	0.75	2.00	1.75	2.00	1.25	2.25	1.50	2.25	2.00
24	1.33	1.00	0.75	1.00	1.25	1.25	2.00	2.50	1.75	2.00	2.25	2.00	1.50	1.50	1.00	1.50	1.50	2.00	1.50	1.75	1.50	1.75	1.75	2.00