MSc Thesis Interaction Technology

Sports Interaction Technology For Training Load Management And Injury Prevention

A case study on hangboard training

Amber Eggengoor

Supervisors
dr D.W.B. Postma
dr. ir. D. Reidsma

August, 2022

MSc Interaction Technology
Faculty of Electrical Engineering,
Mathematics and Computer Science

UNIVERSITY OF TWENTE.

Abstract

Hangboard training improves forearm flexor strength, finger strength, endurance and postural control in a short time frame. This rapid improvement in physical strength is due to the high load used in training. The effectiveness of the high load in hangboard training is researched thoroughly, while the impact of this high load on the athlete is under-explored. During hangboard training, the athletes rely on their finger tendons to hold their body weight. This means a high concentrated load on the fingers and shoulders. Research on injury prevention shows that training with a high load is the most common reason for overloading injuries. Therefore, further investigation should investigate a balance between the athlete's capabilities (internal loads) and the training intensity (external loads). Data from the literature, interviews, surveys and user tests were collected to investigate such balance. Quantitatively, no statistically significant difference was found in performance level if the athlete trained with or without the created feedback system. However, the data does show some effect on the user, which needs further investigation. Qualitatively, an effect has been found on self-evaluation of the athlete as the athlete was more insightful about their performance with the help of the feedback system. Besides the findings for hangboard training, the overall process used during this case study is not yet seen in related studies. The executed steps in the design process are novel and can be replicated for other sports to further explore Interaction Technology for training load management and injury prevention. On a low level, these findings indicate the need for more in-depth research on hangboard training to investigate the suggested framework's steps further. On a high level, there is the need for more expansive research on the design approach used, where the framework is investigated and applied to other sports.

Acknowledgements

Foremost, I would like to thank my supervisor, Dr. Dees Postma, for the support, guidance, motivation, enthusiasm, knowledge and time. The weekly meeting helped spark my inspiration and got me through the thesis process.

Then, I would like to thank all the participants who participated in this research via interviews, surveys or user tests. This project would not have ended like this without the participants' expertise.

Third, my sincere thanks to all the colleagues at Movella who helped me during the thesis by sparking inspiration and insightful discussions.

And last but not least, I would like to thank my friends and family for the support and love I received during the project. Their wise counsel and kind words helped me through, especially during weeks of report writing.

Contents

Chapter 1

Introduction

Climbing performance has been defined as a combination of forearm flexor strength [15], finger strength [7] [8] endurance [38] and postural control [38]. Especially when the route characteristics become more challenging, forearm flexor and finger strength become more important. Improving climbing performance strongly depends upon effective training methods. Hangboard training is one of the most popular approaches to increasing finger, and forearm strength [33] in climbing. Therefore, hangboards have become one of the most used pieces of training equipment for climbers. During hangboard training, it is possible to adjust the training intensity by utilising smaller and bigger holds and exploring grip positions. In addition, it is possible to adjust the resistance by adding or reducing weight. Within this hangboard training, the goal is to increase maximum finger strength by loading the fingers at a very high intensity, often for a short time (repetitions of 7 seconds). This maximum finger strength is not a fixed number but differs per person. Climbers claim that training finger strength has to be prioritised to become a good climber, (1) because building finger strength takes a long time and should be practised in isolation and (2) because, without finger strength, you are not able to grip the 'harder' climbing grips.

The workload during hangboard training focuses on specific tendons in the body (fingers, forearm and shoulders), which can cause acute, abrupt and (unintuitive) unpredictable injuries. Climbers have a difficult time feeling where the boundary lies between safe training practices and high-risk training practices. The interest in better understanding fitting training loads to prevent injuries is often motivated by the decrease in performance, and the cost of the rehabilitation [21]. Besides that, when an athlete is injured, he, of course, cannot optimise and train his skill during this critical rest period, which is not desired and unpleasant. The most crucial component to preventing injuries among hangboarders is the self-perception of their load capacity (for how long can I hang, with what weight, and in what position).

As preliminary research, the current state-of-the-art of IMUs for designing interactive applications in sports has been investigated. The results of this research can be seen in section 5.1 Appendix. It became clear that IMUs are proven capable of measuring athletes' postures and motions. The interaction technology research field can use this opportunity to create meaningful and practical interactive IMU sports applications. However, as the paper stated, each sport requires a different skill-set and training. Therefore, case studies became apparent to maximise the potential of IMU-driven interactive applications. This thesis is a follow-up case study focusing on hangboard training to investigate the process of designing interactive applications to manage training load and prevent injuries. The use of IMUs in sports is a rising approach that seems promising. Therefore, this thesis investigates the implementation of interactive technology in hangboard training, through the lens of IMUs and its capabilities.

When an interactive system could give more insights into an hangboarder's load capacity and weaknesses, it is possible to prevent injuries (prevent overloading) and improve performance (improve the hangboarder's weak spot). Therefore, this thesis focuses on:

- **How can the internal load capacity of hangboard athletes be quantified and effectively communicated to the user?**
- **How can the external load of the athlete be tuned to the internal load of the athlete during hangboard training?**
- **How can interactive feedback benefit the self-perception of the athlete's training load during hangboard training?**

These three research questions will be answered by first diving into the background to understand the nature of the hangboard training. Then, related work will be discussed to gain more insights on hangboard training and to spark inspiration for innovation. Then, the methodology section will follow to find the potential for a novel product, leading to the conclusion and discussion.

Chapter 2

State of the Art

2.1 Background

2.1.1 The hangboard

A hangboard workout is a climbing workout which uses a piece of equipment called a hangboard. A hangboard, also known as a fingerboard, is designed specifically to help rock climbers increase the strength of their climbing holds and grips[1]. There are many hangboards commercially available in stores all over the world. Hangboards come in different sizes and shapes and can be made of different materials. Figure 2.1 shows some examples of non-interactive hangboards, such as Trango Rock [2], Metolius Wood [3], Metolius 3D [4], Metolius Prime [5]. Each hangboard has its advantages and disadvantages and should be chosen by the user based on his capabilities and desires. The prices of these hangboards lay between 40 euro and 150 euro.

(a) Trango Rock Prodigy Training Center[1] (b) Metolius Wood Grips Deluxe II[2] (c) Metolius 3D Simulator[3] (d) Metolius Prime Rib[4]

FIGURE 2.1: Four examples of different hangboards (non-interactive).

Besides these 'standard' hangboards, there are some interactive hangboards available. This thesis investigates the design process of an interactive application for training load management to prevent injuries. Therefore, there are some interactive hangboards which are interesting to look at. In total there are (only) three[6] [7] [8] interactive hangboards commercially available and are visible in Figure 2.2.

The first interactive hangboard worth discussing is the Zlagboard (€200). The Zlagboard is a weight-triggered mechanism for smartphones to track hang-times and pull-ups

[1] https://www.masterclass.com/articles/hangboard-workout-guide
[2] https://www.amazon.com/dp/B01CK219W8?tag=outdoocom-20&linkCode=ogi&th=1&psc=1
[3] https://www.shorturl.at/ksFO4
[4] https://www.shorturl.at/qGPX7
[5] https://www.amazon.com/dp/B083NH5N7G?tag=outdoocom-20&linkCode=ogi&th=1&psc=1
[6] https://zlagboard.com/
[7] https://climbro.com/
[8] https://entralpi.com/

(a) Zlagboard[1] (b) Climbro[2] (c) Entralpi[3]

FIGURE 2.2: Three examples of different hangboards (interactive).

automatically. Besides monitoring the climber, the system has an app that provides training plans matching the user's goals. Thereby, the user can track his progress, create hang-time competitions with friends and design his own sessions with certain goals. The interaction between the board and the user is created through the IMU in the smartphone which measures tilt differences and thus knows if the user hangs on the hangboard (the weight makes the board tilt).

Compared to the Zlagboard, the smart hangboard Climbro (€679) is more focused on performance and load. The Climbro app provides competition, hang-time progress and training schemes and insights into the climbers' physical state. Next, the Climbro app not only functions as a stopwatch but also provides real-time feedback on applied forces and guides the user through the exercise. In the Climbro board, force sensors are integrated, measuring if the user hangs on the board and where the user has placed his hands (only on the horizontal axis).

The Zlagboard and the Climbro hangboard are interactive boards with technologies integrated within the board. This means that the climber cannot change boards and can't use the technology without using the provided hangboard. Entralpi (€145) works with external technology (force plate) that can measure the climber's strength on any hangboard. Based on the data from the force plate, the mobile app provides exercises, tests, automatic analysis, benchmarks and tips.

2.1.2 The hangboarder

Informal semi-structured interviews (with consent forms) were held with hangboarders in The Cube[9] (boulder hall in Enschede) to gain some insights from the user itself. Eight athletes had time and were willing to talk about their experiences and knowledge of hangboard training. All eight athletes hang at least two times on the hangboard per week. The age of the athletes ranged from 20 to 27 years. From these interviews, five main insights came forward on how hangboarders train and what materials they use:

- Three different grip positions are often used: open hand, half crimp and full crimp (see figure 2.7).
- Training in sets (x times 7-10 seconds) or max hangs (not more than 30 seconds).
- 90% of max for power endurance phase.
- Generated training schedules are used on applications such as Crimpd[10]
- Materials used: hangboard, pulley (to decrease weight), brush, timer, set of weights and harness (to increase weight), chalk and phone (music and training schedule).

[9] https://cubebouldergym.nl/
[10] https://www.crimpd.com/

Besides how hangboarders train and the materials they use, more focused questions in the interview referred to the awareness of the hangboarder's posture and the pros and cons of hangboard training. These questions made it clear that the hangboarders had difficulty being aware of their posture. Sometimes they try to resolve this problem by using cameras or asking a friend/coach to ensure a correct posture during the training. Then as a follow-up question, the hangboarders are asked to think about where (in their opinion) handboard training is lacking. From these questions, pros and cons and a few interesting statements came forward:

Cons	Pros
Have to add weight for max hangs on two hands, but too weak for one hand hang.	Huge increase in finger strength in a small time frame.
Don't take the time to do hangboard training properly.	Prevents pulley injuries.
Hangboard training is boring.	Targeted (isolated) training for finger strength
I can get injured quite easily.	Hangboard training can be done everywhere and at any time.
	It is not expensive to buy one of my own.

FIGURE 2.3: The pros and cons of hangboarding according to the interviewed hangboard athletes.

- *"When doing max hangs, the effort is so intense that your perception of your surroundings mostly fades, so external motivation would probably not help much."*
- *"I could use a camera, but I wouldn't know what good form looks like"*
- *"I would like recommendations on technique based on force recruitment statistics. Avoiding over gripping and recommending when to increase/decrease weight. Possibly tracking day fatigue or long-term injury prevention by noticing decreases in performance."*

In conclusion, hangboard training is a high-load training method that can cause acute injuries if the training load is not managed properly. Currently, the training load is subjectively set via coaches, trainers and smartphone apps. By providing more guidance to the athlete in choosing a fitting training load, injuries can be prevented.

2.1.3 Key Performance Indicator (KPI) analysis

As mentioned in the introduction, climbing performance is associated with forearm flexor strength, endurance and postural control. Hangboard training is a popular and often used training protocol used by climbers to increase their arm/finger strength rapidly. Hangboard training protocols are focused on maximising weight and hang time, and minimising edge sizes [33]. The study of Mundry [33], Stien [42], Hermans [19] and Kingsley [26] are example studies that have investigated the effects of training with and without an hangboard as a climber. All four studies found a significant improvement in the climber's grip strength and climbing endurance over a period of 4-8 weeks. The research of Medernach [31], which focuses on the performance increase of boulderers by using an hangboard, complements by also finding a significant increase in performance in the group which trained with an hangboard for 4 weeks. Besides studies that focus on improving climbing or bouldering performance, health care studies [5] have been focusing on the improvement of wrist and forearm strength by using an hangboard, which also found significant improvement in the participant group who used the hangboard for 4 weeks. So, it can be concluded that the hangboard is an effective way to improve strength, and performance over a small amount of time (+/- 4 weeks), for both traditional climbing and bouldering. Several studies have focused on improving the hangboard to make it more effective. Anderson [4] designed an innovative hangboard and had a significant and unique result for the sport of climbing as his design also proved to reduce injuries. Anderson investigates the design of the hangboard and suggested on specific features such as a) equation-driven grip edge profiles, (b) drafted pockets, (c) novel grip designs, (d) improved grip geometry, and (e) improved texture. However, Anderson did not dive further into training methods. Besides proving the effectiveness of using an hangboard during climbing/bouldering training, the variables measured and researched by the above-mentioned related papers can help to find the indicators which together form the hangboarder's performance. Indicators measured and mentioned are, grip strength [4][5][26][31][33], hang endurance [26][31][33], shoulder strength [4][19], and back strength [19]. These four key performance indicators are considered important and can explain the hangboarder's performance.

2.1.4 Training load

Training load can be mistaken for the training intensity: reps, duration, distance, etc. However, the total training load is more than these external training loads. The training-process framework of Impellizzeri [21] includes essential measurable components necessary for monitoring and controlling the whole training process: (1) the external load, (2) the internal load, and (3) the training outcome [41][13][21], as can be seen in figure 2.4 below.

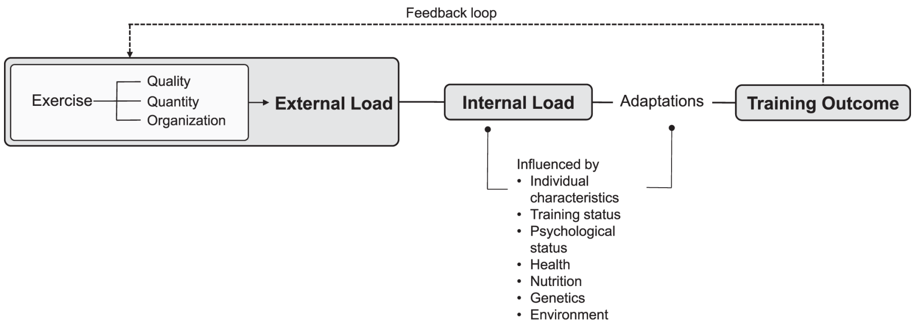


FIGURE 2.4: Training process framework and measurable components for monitoring [21].

It is essential to understand the external loads to get a better idea of the internal load of an athlete [32]. As said before, the external loads represent all the training modalities imposed on the athlete. Combing the external load with the individual characteristics like sleep, stress, nutrition, etc., a full image of the athlete's experience (internal training load) can be drawn. In addition, it is essential to balance the external and internal loads to get the desired training outcome [32][3][1]. This is because the external loads should not stress the internal load too much to prevent overloading and injuries but should stress the individual enough to gain improvement during the training and prevent underloading [16]. It is important to monitor if this imbalance between internal and external loads happens as identical external loads may elicit different internal loads per day (due to for example stress, nutrition or sleep) [1].

According to the interviews that were held with hangboarders, finger injuries seem to happen without any warning signs. Hangboarders claim that one minute they are feeling psyched about how strong they have become and are enthusiastic about their progress. The next, their finger tendon snaps and the trauma hamper the hangboarder even in simple daily tasks. According to the participants, finger injuries in hangboard training are unpredictable and feel abrupt. This causes fear among some hangboarders, especially when finger injuries have happened to them. Figure 3 shows an abstract representation of the hangboarder's internal load vs the external load. Figure 2.5 visualises the abruptness of finger injuries (red arrow) and via the gradient, it is visible that hangboarders would like to train in the green zone (near the red arrow) to make as much progress as possible but do not get injured (dashed zone).

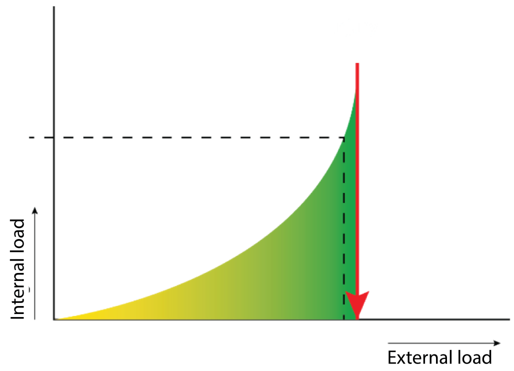


FIGURE 2.5: Abstract representation of internal load (y-as) vs the external load (x-as) to find the training load (area under the curve). The red line indicates tendon injury.

The interviewed hangboarders claim that there are three external trainings loads that can be changed during hangboard: duration, weights and crimp type (Figure 2.7). These variables have an inverse relationship with each other. So for example, when more weight is added, it is likely that the athlete is not able to hang for the same duration and crimp type as when there was no added weight. Therefore, to achieve high volume in training (long duration), weight should be lowered and a fitting crimp type should be chosen. The same applies for training with a relatively hard crimp and additional weight, the duration time should be reduced in order to prevent overloading. According to the hangboarders, it is hard to play around with the external loads, as it is hard for them to estimate which intensity (crimp type and added weight) and volume (duration) is fitting their current internal loads. From the interviewed hangboarders and the book called Beastmaking [14], five ways to play around with the external loads of hangboard training are found and listed in figure 2.6 below.

	Decrease training intensity	Increase training intensity
1	Use bigger holds	Use smaller holds
2	Shorter hang time	Longer hang time
3	Reduce weight	Add weight
4	More fingers/hands	Fewer fingers/hands
5	Longer rest time	Less rest time

FIGURE 2.6: Five ways to adjust the hangboard training intensity.

Accurate monitoring of the athlete's training load is essential for an effective and efficient training process. The adequate training stimulus contributes to an improvement in physical strength and condition for the athlete. In contrast, an excessive training load can increase the risk of injury and reduce the performance [44] [16]. There are two main types of injuries, overuse injuries and acute injuries [35][37][49]. Overuse injuries result from prolonged, repetitive motion, particularly common in endurance sports such as running or cycling. Acute injuries, on the other hand, is an injury that suddenly occurs and is often unpredictable. The most significant difference between overuse and acute injuries are the injuries' signs and symptoms. Acute injuries occur suddenly and unexpectedly with severe pain (broken leg, muscle tear, etc.). In contrast, overuse injuries occur over a relatively long period, where the pain emerges if the athlete exercises more. The athlete always strives to train on peak performance to gain the most. Training loads below this peak performance result in a low adaptation, while training loads above this peak performance result in overloading or worse, injury. Usually, when the athlete faces a plateau or drop in performance, he intends to increase the externals loads of the training. However, by increasing the external loads without understanding the internal loads, an imbalance can occur where overloading and injuries are likely to happen [44] [24]. The study of Halson [18] complements this and has indicated that it is best to use both internal and external training load as an indicator of fatigue to prevent overloading. Nonetheless, if the athlete reaches an undesirable state due to overloading, then rest is the best-known treatment [11] [20].

2.1.5 Posture

The posture of the hangboarder's fingers/hands is one of the most important aspects, as the training regime is mainly focused on the fingers. The indicator *grip strength*, which was earlier mentioned, can be explained by how long the hangboarder can hold the grip, before he slips away. This "slipping-away"-process makes the fingers/hands prone to injuries. The three most common crimps are visible in figure 2.7 below.

Figure 2.7: The three most common crimps[11].

Besides the fingers, the shoulders have to deal with great load as well [47]. It is advised to hang with 'active' shoulders as visible in Figure 2.8, to avoid shoulder injuries. This active posture can only be maintained with good core and shoulder strength. According to the participants of the interview, if there is little core and shoulder strength, it is not possible to hangboard with the correct stability and consistency. Which makes the athlete more prone to injuries. The positions mentioned in Figure 2.8 allow the athlete to load the muscles instead of the joints. It is important to monitor when the internal loads of

[11] https://www.climbinganchors.com.au/hangboard-training/

the athlete start to respond to the external loads, to detect overloading and the prevent injuries [1].

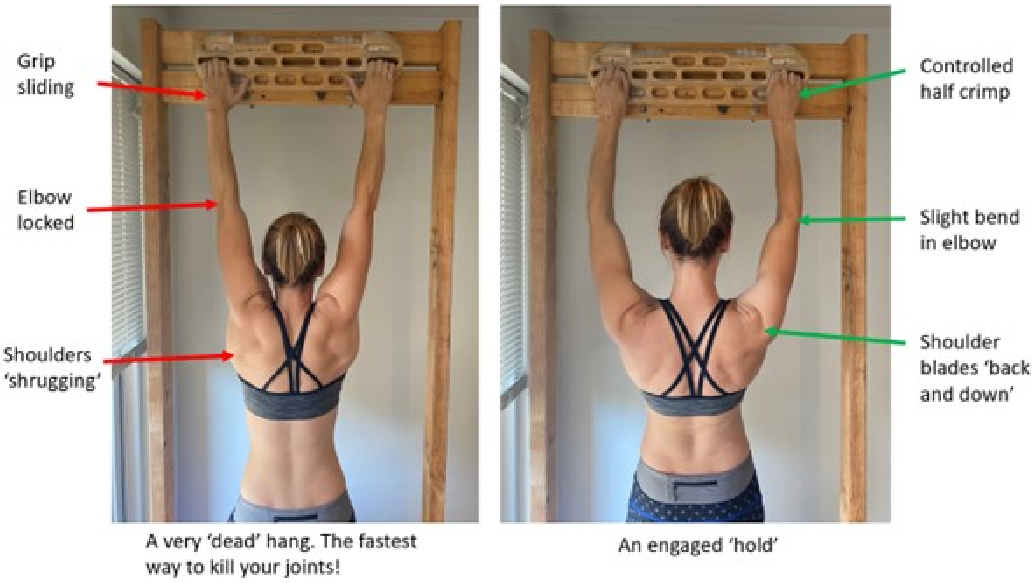


FIGURE 2.8: Hanging with bad form vs hanging with good form.[12]

As mentioned in the previous section, most hangboarders try to hang with the correct posture. However, what this correct posture exactly means is not set in stone. From interviews, it became clear that sagging into bad posture occurs slowly and imperceptibly. The interviewees state that at 'some' point the athlete knows that he has sagged too much and then considers stopping hanging to prevent injuries. However, this threshold is subjective and self-chosen and it might be possible to identify this sagging earlier with the help of some sensors. From the study in section 5.1 Appendix, it became clear that IMUs have the potential to become an helpful tool to quantify this threshold to make it more clear to the athlete when their posture is sagging into bad posture, which is an indication for the plateau of their internal load capacity. Sensors are more likely to sense the sagging process faster than the athlete himself, as sensors are able to detect even the slightest change in motion. The most important part of determining this threshold is to first find out what 'correct' posture is and what the characteristics are. Hangboarders claim that each athlete has his own 'correct' posture due to anatomy differences per person. Therefore, a potential system has to calibrate towards the personal characteristics of a hangboarder in order to find the correct posture. Calibration of wearable sensors via static poses, which is a popular method for calibration [45], might not cover enough body structure information for hangboarders. Interviewees claimed that even hangboarders with the same arm length might have a different correct posture, due to the body's maximum flexibility and muscle power. For this case study, a more fitting way to calibrate the system would be to provide instruction to the user to find the individual 'correct' posture. The saved correct posture can be set as a threshold to then monitor any deviations from the start value. The instructions[13] : for the correct hang posture can be seen in figure 2.9 below.

[12] `https://www.climbinganchors.com.au/hangboard-training`

[13] https://www.blackdiamondequipment.com/enCA/stories/experience-story-esther-smith-shoulder-maintenance-for-climbers/

1. Lie belly down with arms overhead and palms down.
2. Shrug the shoulder blades up and reach with your hands as far overhead as possible, while keeping contact between your hands and the floor.
3. While keeping your palms in contact with the floor, rotate your upper arms outward by turning your elbow creases toward the ceiling.
4. While maintaining that position in your arms, gently slide your shoulder blades down your back to the bottom of your available range of motion.
5. Finally, make fists with your hands, and attempt to lift your hands off the ground, while keeping your fists positioned palms-down and your elbows nearly straight.
6. This final position is "hanging right." You should feel your muscles lightly working to press your shoulder blades securely against your rib cage, while also feeling as though you could hold/squeeze a tennis ball in each armpit (this is the feeling you get when your rotator cuff and scapular sling muscles are engaged).

FIGURE 2.9: 6-step instruction that helps the hangboard athlete to find a correct hang posture[14].

2.1.6 Conclusion

In conclusion, before hangboard posture can be evaluated; it is essential to understand the correct posture and to know acceptable deviations (threshold). If unacceptable deviations are found, the external training load should be adjusted in order to balance the internal training load of the athlete. In case of hangboard training, adjusting the external training load can be done via five ways: adjusting the hang time, adjusting the rest time, adjusting the crimp type, adjusting the grip size, and adjusting the weight.

From the previous section three main user problems came forward:
- It is hard for hangboarders (especially for beginners) to find the right external loads so that they do work out but do not overload.
- It is hard to evaluate and correct the right (active) posture.
- It is hard to grasp for hangboarders when to let go of the grip at the moment that their internal loads and external loads start to imbalance to prevent overloading.

Besides the problems that are identified, based on the previous section a few design constraints should be taken into account.
- The solution should be easy to set up (as hangboard training can be and is done everywhere. From a tree branch outside to a doorframe inside.
- Most hangboard exercises are in repetitions of 7 seconds, so the interaction should be fitting.
- Each hangboarder has different internal loads, the system should work for all.
- Design prototypes with an IMU lens, thus with measurement capabilities of IMUs.

2.2 Related work

The previous section discussed the hangboard training load, consisting of internal and external loads. Subjective and objective data can explain the external and internal loads.

[14] https://www.blackdiamondequipment.com/enCA/stories/experience-story-esther-smith-shoulder-maintenance-for-climbers/

Subjective data explains an athlete's psychological or physiological state from their point of view. Objective data explains data about an athlete that is measurable by observation or testing. Mapping objective/subjective data and internal/external load, results in a design space as visible in figure 2.10.

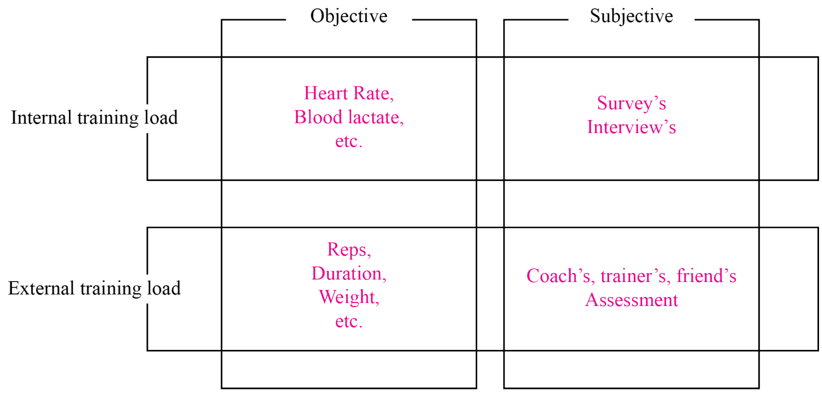


FIGURE 2.10: Design space, subjective/objective and internal/external training load.

From the previous section, it became clear that the hangboarder leans towards the desire for objective data to fit better external loads, the correct (active) posture and to grasp better when the internal and external loads become imbalanced. However, before starting ideating on a novel product for hangboarders, it is helpful to look at existing and related work to gain more insights and spark inspiration.

2.2.1 Monitoring training load systems

An often-used method to quantify the subjective internal training load is asking the athlete to rate how he felt about the intensity of the exercise (perceived exertion). Monitoring the athlete's perceived exertion per session would assure optimal training adaptation and reduce the risks of overloading. The Rating of Perceived Exertion (RPE) scale is based on a range between 6 and 20, in which 6 refers to *no effort* and 20 refers to *maximum effort* [46] [6]. The RPE scale is designed to give a fairly good estimation of the actual heart rate of the athlete during the training. The heart rate can be found by multiplying the RPE scale score of the athlete by ten [46] [6]. Another quite similar tool is called the Modified RPE-scale. This scale ranges from 1 to 10, in which 1 refers to *no effort* and 10 refers to *maximum effort*. The main difference between the RPE scale and the modified RPE scale is that the modified RPE scale is measured by the individual's breath [17]. Both methods have the advantage of being an easy system with no need for technology. However, the athlete is trusted by filling in a number according to his perceived exertion. Therefore, the score depends on a subjective assessment, and the intersubject comparisons may be inaccurate [46] [6] [28].

Besides quantifying subjective internal training load, several studies focused on developing methods that use objective measures to quantify internal training loads. Banister [2] created a model called TRIMP, which quantified internal training load based on the duration of the session with the mean heart rate. Other methods used ventilatory [30] or blood lactate [22]. To overcome the limitations of the separate variables, it is recommended to use more measures or add subjective quantifying systems such as RPE scales as mentioned above [45].

The external training load is often prescribed in the training program, either by an app (objective) or by a trainer (subjective). An essential part of developing a training program is understanding the determinants (limiting factors) [21]. Figure 2.11 visualizes Impellizerri's operational framework in the context of injury prevention, in which the determinants are the factors related to injury occurrence. A trainer can use the framework to create a fitting training program for their athlete(s). The external training load should be based on (1) the evidence available (internal load), professional knowledge, own experience and the understanding of the athlete's characteristics.

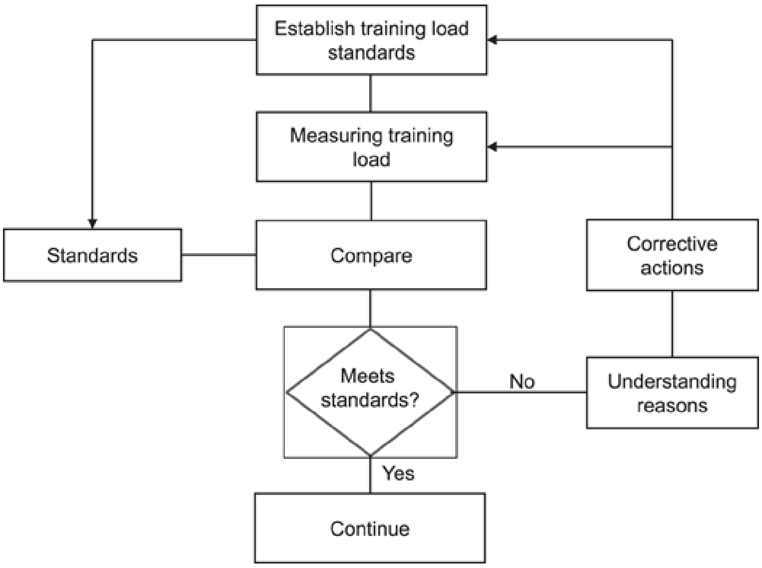


FIGURE 2.11: Operational framework integrating the training process, monitoring, and control of the training load for injury prevention [21].

2.2.2 Posture evaluation systems

Currently, the athlete's coach/trainer has an important role in posture and motion recognition during training. Considering this task without the use of technology, the trainer observes and assesses the athlete with his own eyes and from experience and knowledge he provides (fitting) feedback. Enhancing the trainer by the use of technology can help him to provide more feedback (quantitatively) and preciser feedback (qualitatively) [43] [51] [12].

There are several studies which investigated posture evaluation in sports. The study of Raweshdeh investigated preventative feedback in overhead sports with the use of IMUs to collect data on the posture of the athlete [36]. The study of Yu [50] investigated on ways to detect turn motions of alpine skiers. The study of Wu [48] investigated a posture recognition system for yoga athletes. All three studies are rather similar, as they all investigated ways to quantify a value, which is often assessed qualitatively by a trainer or coach. Example values are for example shoulder rotation [36], pelvis rotation [50] and body orientation [48]. In these studies, the variables are seen as input for the feedback system. For example, in the study of Raweshdeh [36] the shoulder motions are tracked to see if the athlete's performance is decreasing. The athlete is warned when the performance decreased till such a level that the athlete is prone to injuries. This performance decrease is inherited from posture deviation from the correct posture. The study of Wu [48] uses algorithms to classify the postures of the athlete. After classification of the posture, the system was able to provide feedback to the learner in order to improve his posture. However, without the algorithm, it is not possible classify the athlete's posture with an high accuracy as every athlete has its own individual characteristics [48].

The important aspect which can be learnt from these studies is the importance of having a start value. Deviation from this start value can be measured and quantified. In the situation in which the trainer assesses the athlete, the trainer 'knows' the start value of the athlete by heart from experience and knowledge. However, this experience and knowledge is not something that can be suddenly incorporated into technology. Therefore, it is important to set start values and understand acceptable deviation before being able to give proper feedback. In training without technology, the acceptable deviation is subjective and hard to grasp for the athlete. Quantifying this deviation with sensors can help the athletes by having more objective feedback and something to hold onto.

2.2.3 Conclusion

From existing training load monitoring systems it can be learnt that it is important to balance the internal and external load of the athlete. There are several systems which are often used in research to monitor the internal training load through surveys and interviews. However, these are subjective measures and can include lots of biases. Besides, subjective measures, there are some quantitative measures, which include heart rate monitoring or training duration. However, those quantitative measures are not as explored as the qualitative measures. It is important to monitor the internal training load as accurate as possible, before being able to choose fitting external training loads. The better the balance between the internal load and external load, the better the training outcome and the more efficient progression the athlete makes.

From existing posture monitoring systems, it can be learnt that the right posture should be set as a start value before a deviation from this posture can be measured. Just as with the training load monitoring systems, those measurements are often done via qualitative measuring methods such as interviews and surveys. However, quantifying posture measurements is an upcoming research topic and seems to have lots of potentials. Indicators of these deviations can be different per sport, as every sport has its nature and aspects. Therefore, it is important to investigate the most important indicators per sport. Next to this, most of the existing systems provide only warnings to the user and do not offer advice for adjustments. Providing the athlete tips for adjustments can be done before the warning is given, to give the athlete the opportunity to improve on time.

2.3 Discussion

From the background research it becomes clear that a lot of measurements are done qualitatively in hangboard training. This could be because technology for hangboard training is not yet explored that much, as there are not many papers published on hangboard training in specific. Now climbing has become an Olympic sport, it is likely that more research will follow. This thesis will use a co-design approach to explore interaction technology in hangboard training to investigate a training load management system to prevent injuries. The framework, which is created for this thesis, is a combination of the two frameworks of Impellizzeri [21] and can be seen in figure 2.12. It is a combination as Impellizzeri's frameworks are focused on adjusting the external loads after the internal loads were measured, to reach a certain training outcome. However, this did not fit this thesis perfectly and a new framework was created. A readiness test is proposed to measure the current state of the athlete's internal load, before being able to set the external loads of the training, to avoid the risk of overloading at the beginning of a training routine. Then, the internal load of the athlete will be monitored during the training, to see if adjustments in external loads are needed to reach the desired training outcome.

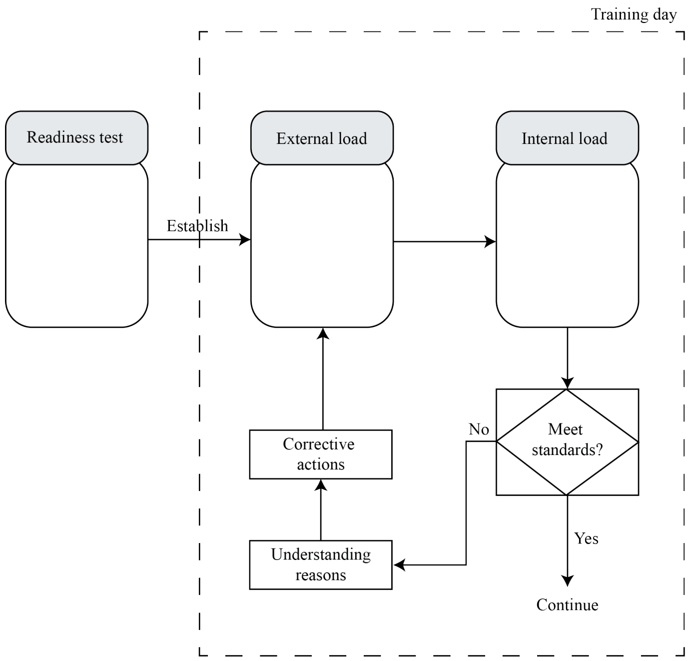


FIGURE 2.12: Proposed framework based on the two frameworks of Impellizzeri [21].

The proposed framework in figure 2.12 is not yet filled as there are some variables not (yet) determined. The *internal load indicators*, the *internal load standards*, possible *failure reasons*, and applicable *corrective actions*. The next section will dive further into these variables and will apply the framework to hangboard training. By applying the framework to a specific sport, a step-by-step plan to fill the framework is developed which can later be applied to other sports. Besides, the steps taken for hangboard training can be further deepened by future research.

Chapter 3

Methodology

This thesis focuses on developing a design approach for injury prevention, with hangboard training as a case study. In this approach, the user is centred and involved through different methods. This participatory approach is also called: *Co-design*. Co-design is a design approach in which the participants are treated as equal collaborators in the design process. The design decisions are postponed until after gathering the feedback from the participants. Gathering their opinion can be done via multiple methods. For this thesis, the user is involved via semi-structured interviews, lo-fi prototype discussions, expert meetings, surveys, a design workshop, and user tests. Those methods are not single events but are together the co-design process, which can also be seen in figure 3.1. The upcoming sections will dive further into the three phases, their methods, setups and results.

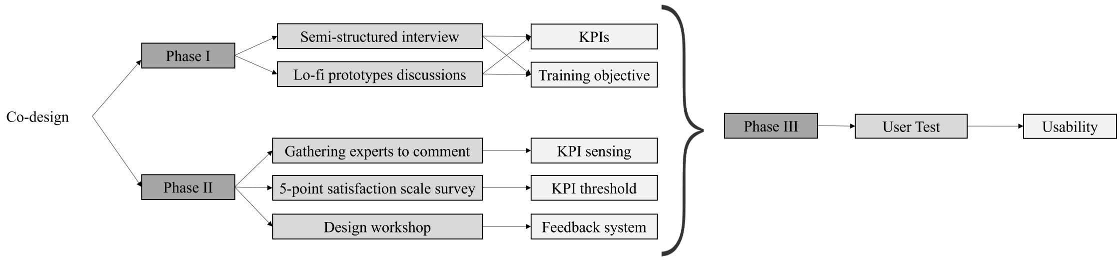


FIGURE 3.1: The co-design process, consisting of three phases.

3.1 Phase I: Investigating user goals and KPIs

Before being able to prevent the athletes from getting overloaded in training, the internal load indicators should be found and should then be monitored during training. The internal load can be explained by the term Key Performance Indicators (KPI). The KPI is a quantifiable measure which is seen as one of the most important indicators of the current performance level of an individual[1]. Through academic research four KPI's were found and stated in section 2.1.3 Key Performance Indicators, and are listed below.

- Grip strength [4][5][26][31][33], *The athlete's ability to hang for a certain time without slipping away the hand from the grip.*
- Shoulder strength [4][19], *The athlete's ability to hang for a certain time with active shoulders.*
- Back strength [19], *The athlete's ability to hang for a certain time with a stable core.*

[1] https://www.optimizesmart.com/understanding-key-performance-indicators-kpis-just-like-that/

- Hang endurance [26][31][33], *The athlete's ability to hang for a certain time, in the correct posture (correct hands, correct shoulders, correct core stability).*

The specification and complementation of these through research found KPIs will be done via user Research in the form of a lo-fi test.

3.1.1 Methods

Semi-structured interview

A semi-structured interview is a data collection method that relies on asking questions within a predetermined thematic framework. As the interview is semi-structured, the questions are not set in order, or phrasing [29]. The semi-structured interview aims to confirm the findings found in the previous sections' literature and explore hangboard training further. The interview results will be analysed via a thematic analysis, where the data is examined to identify common topics, ideas, and patterns.

Lo-fi Prototypes

During the semi-structured interview, two lo-fi prototypes are shown to the participants, as visible in figure 3.2 and figure 3.3. Low fidelity prototypes are simple prototypes with which a high-level idea or concept can be explained to the participants. Lo-fi prototypes are especially useful in the early design processes as they find out what the user thinks about the idea before it is fully worked out [29]. This means that much time is saved by involving the user at the start of the development process, to prevent missteps in the early phases. The lo-fi prototypes aim to test the idea and the functionality and explore implementation potential [29].

3.1.2 Setup

Nine participants participated in the lo-fi test. The participants' poule ranged from 18 till 27 years old with a mix of female (5) and male (4). All participants have 2+ years of experience with wall-climbing and bouldering, work out on the hangboard at least twice a week, and practice with the hangboard for over three months. The lo-fi testing took place on the UTrack of the University of Twente, where a hangboard was placed in the outdoor gym. The participants got five Xsens DOT sensors strapped on after filling in the consent form. Two prototypes were shown and discussed via a semi-structured interview, as visible in figure 3.2 and figure 3.3. The goal of the lo-fi test is to analyse the Key Performance indicators during hangboard training (KPIs). Besides, the lo-fi testing helps (1) to get confirmation on the user problems stated in section 2.5 conclusion, (2) to explore possibilities for sensor placement (comfortability), and (3) to gain insights into the implementation potential of Interaction Technology during hangboard training, by showing the participants the two interactive prototype ideas.

FIGURE 3.2: Prototype 1: visualising stability.

FIGURE 3.3: Prototype 2: KineXYZ models.

3.1.3 Results

The interview brought a lot of new valuable insights. The participants talked most of the time about their experiences with hangboard training, both as an athlete and a trainer. The lo-fi prototypes shown during the interview helped to spark inspiration and give the user more meaning. Six topics are identified based on the examination of the collected data.

First topic: **user problems**. The participants confirmed that hangboarders have difficulty finding the right workload and maintaining a correct hangboard posture. Both difficulties relate to not knowing when to stop with an hangboard exercise to prevent injuries. In preventing injuries, the athlete must understand his body limit. This means that he should be able to label pain as "good pain" (i.e. something you should push past to achieve your goals) or as “bad pain” (i.e. something you should listen to as a sign of overdoing it)[2] to prevent injuries.

Second topic: **load capacity**. It is stated that the weakest link (shoulder strength, core strength or finger strength) makes the hangboarder fall during an hangboard exercise. The hangboarder aims to strengthen this weakest link to increase his performance. The participants mentioned three important links during hangboard training:

1. Shoulder strength, active shoulder posture during the hang.

2. Core strength, stability and control during the hang.

3. Finger strength, maintaining the right crimp during the hang.

The participants claim that the hangboarder’s muscles start to vibrate when it comes close to the maximum internal load capacity. This vibrating within, for example, a green doughnut (lo-fi prototype 1) could indicate changes in body posture. It thus might indicate to the athlete how stable his hang was or could give a warning when the athlete gets too unstable (prevent overloading). However, it is claimed by the participant that this indicator might work differently per person.

Third topic: **modality of feedback**. Both lo-fi prototypes made use of visuals to represent the motion capture data. The participants were enthusiastic about having graphs or representations of their performance so that progress over time could be seen. The prototype that uses a sticky figure as a representation of the athlete during the hang was received well, and using colour codes (red, yellow, green) on different joints or limbs was imagined to help understand what joint or limb needs improvement. The participants have trained with audio/sound feedback. However, that feedback was focused on duration (hang or rest) or motivation (music). Haptic feedback is not as known as auditory and visual feedback among the participants. After discussing the haptic feedback modality, it becomes clear that haptic feedback does not fit in a hangboard environment. The most important reason was that hangboard training focuses on tiny tendons. Therefore, additional motions (vibrations), even small ones, could be critical for the athlete.

Fourth topic: **content of feedback**. One participant mentioned that it is (currently) hard to give precise quantitative feedback during hangboard training. Qualitative feedback statements such as ‘lean a bit to the right’ are often used to provide feedback to the athlete. One participant states that adding precision in hangboard training by using sensors similar to those used in the lo-fi testing could help provide more precise and objective feedback to improve the athlete’s learning and performance.

Fifth topic: **sensor placement**. According to the participants, none of the placed sensors was uncomfortable or annoying during hangboard training. Due to the lightweight and small size, the participant marked them as pleasant wearables. Figure 12 visualises the sensor’s real-world location changes if the hangboarder saggs from a ‘good’ posture to a ‘bad’ one. Both sensors on the arm (upper arm and forearm) rotate inwards, the sensor on the pelvis shifts downwards, and the sensors on the shoulders move (shift and rotate) towards each other. However, the difference between ‘good’ and ‘bad’ posture is slightly exaggerated to make this point. Nevertheless, as the sensors are accurate, the slightest difference in location can be detected and help the athlete reach and maintain a good posture.

[2] https://www.pthealth.ca/blog/how-to-tell-the-difference-between-good-and-bad-pain/

(A) Good hang posture

(B) Bad hang posture

FIGURE 3.4: Sensor placement during good hang and bad hang posture.

Sixth topic: **additional remarks**. The participants mentioned multiple times that the posture of the hangboarder highly depends on its anatomy (finger length, arm length, etc.). Therefore, it is important to consider a calibration per person on what is 'good' before being able to label 'bad' movements or posture. Next, one participant explained his worry about false indications, as he for example holds his breath to push that bit extra. The last remark not yet mentioned is the importance of having a threshold as a hangboarder to calculate, for example, 70% of their internal load capacity to train for endurance. From this, two new ideas came up.

- A measurement system that can be used by the hangboarder each time he starts hang boarding (personal purchase). Then he could measure his strength on that specific day to train with a fitting workload.
- A measurement system can be used every 6-8 weeks so that the hangboarder can measure his progress over these weeks (climb association purchase). The hangboarder can train according to the strength report.

The sensors were placed on the participants as visualised in figure 3.20. Example data of one participant with five sensors can be seen in section 5.2 Appendix each sensor can be seen below. The graphs show the acceleration in the x-direction (blue line), y-direction (orange line) and z-direction (grey line) over a certain time period (32 seconds). In total 6423 data points are collected for each sensor (2141 data points for each of the 3 different directions). From the collected data a difference between good and bad hang posture is clearly visible. After time sinking the data with the recorded videos of the athletes, it is possible to segment the data into six different phases, 1) Preparing for the correct hang pose, 2) Holding the correct pose, 3) Sagging into the bad pose, 4) Retracting into the correct pose, 5) Sagging into the bad pose and 6) Getting off the hangboard. These six phases are visible in figure 3.5 below.

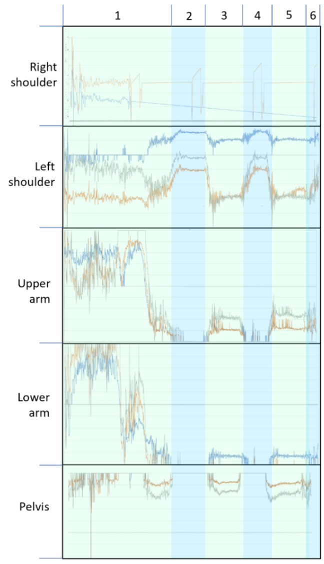


FIGURE 3.5: Segmented data of five Xsens DOTs on one participant.

Considering an automated computer system that analyses these data segments, it would be possible to create a retrospective feedback system that outputs a report. (1) The total hang time, (2) the time frame the athlete hangs in the correct posture (in which correctness is determined based on the deviation from the correct posture), (3) the moment when the athlete sags out of the correct posture and (4) the stability of the body (how controlled the body is).

3.1.4 Conclusion

KPIs

Based on the confirmation of the participants, the three main user problems during hangboard training are as follows:

1. It is hard to find fitting external loads for the hangboarder's internal loads.
2. It is hard to evaluate and correct towards the right (active) posture.
3. It is hard for hangboarders to know when to stop with hangboard training as an imbalance between external and internal loads is hard to grasp.

The first and second problems can be solved by understanding the internal training loads of the user to find fitting external loads later. From the lo-fi test, it became clear that there are three insightful KPIs for internal training load: *shoulder strength* (sagging of the shoulders), *finger strength* (slipping away of the hands) and *core strength* (shakiness of the back). One additional KPI mentioned by research: hang endurance, can be integrated into the other three KPIs as the hang endurance of the hangboarder depends on the weakest link of the hangboarder. By monitoring the other three KPIs and finding the weakest link, hang endurance is found too. Therefore, three KPIs are the foundation for measuring the internal load of the hangboarder, as visible in figure 3.6.

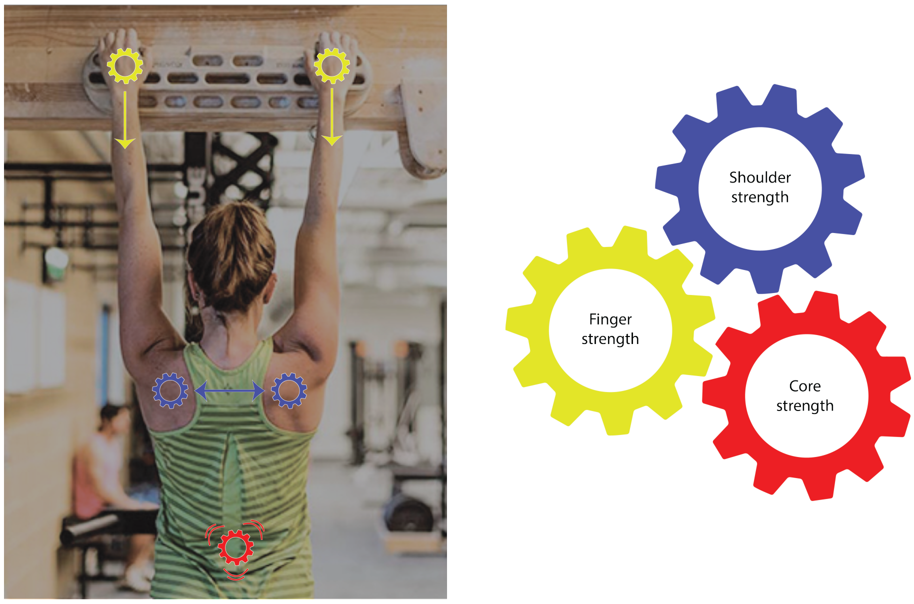


FIGURE 3.6: The three KPI's for the internal load of the hangboarder. (Source[3] of the original image of the hangboarder)

Training Objectives

It is important to consider the training objectives of an hangboarder in order to understand the desired training outcome. Based on the athlete's desired training outcome, it can be decided where and how feedback should be given and based on which variables. In section 2.1.2 it already came forward that there are two training types for hangboarders. The interview held with the participants helped to specify these two types further:

- *Hang in sets.* This training type focuses on building strength and endurance by making certain hang repetitions in sets [14]. For example, a set can be a hang of six seven-second-hangs with 3 seconds of rest. The training could consist of multiple sets with 3 minutes of rest between the sets. During this training type, it is important that the hangboarder can hold the repetitions in the correct form without failure. If the hangboarder cannot hold, there are three possible ways to adjust the external load of the training: change the duration, change the crimp type, or adjust the weight. The KPIs mentioned in the previous section indicate which link in the hangboarder's system is the weakest. The athlete can be advised on possible training adjustments via a feedback system. As it is key in this training type to hold on to the hangboard for 7 seconds, each KPI is important to monitor and must meet its own KPI standard to provide the user with fitting advice.

- *Max hangs.* This training type focuses on building maximum strength by letting the hangboarder hang till he meets 'failure'. The athletes train to failure in max hang training, but not a total failure. According to interviews and online research, failure in max hang training is defined as losing shoulder engagement[4,5]. The slipping away of the fingers and the core strength are in this training not as big as a problem. This

[3] https://www.grassrootsphysicaltherapy.com/physical-therapy-treatment/2017/
[4] https://mojagear.com/building-maximum-finger-strength-with-hangboarding/
[5] https://pitchsix.com/blogs/academy/academy-hangboard-shoulder-engagement

is because the goal of the athlete (in this training type) is to hang till he falls off the board which automatically protects the athlete from getting injured in the fingers and the back. However, hanging without active shoulders does not automatically make the athlete fall off the board, and can still cause shoulder injuries. Therefore, for this training type, the KPI of shoulder strength is the important indicator for the hangboarder to decide when to stop the hangboard training to prevent injuries.

Both training objectives have their nature and aspects, as mentioned above. Both can ask for (partly) a different feedback design. Therefore, the proposed framework of figure 2.12 is applied to both training objectives according to the findings of the lo-fi test and can be seen in figure 3.7 and figure 3.8.

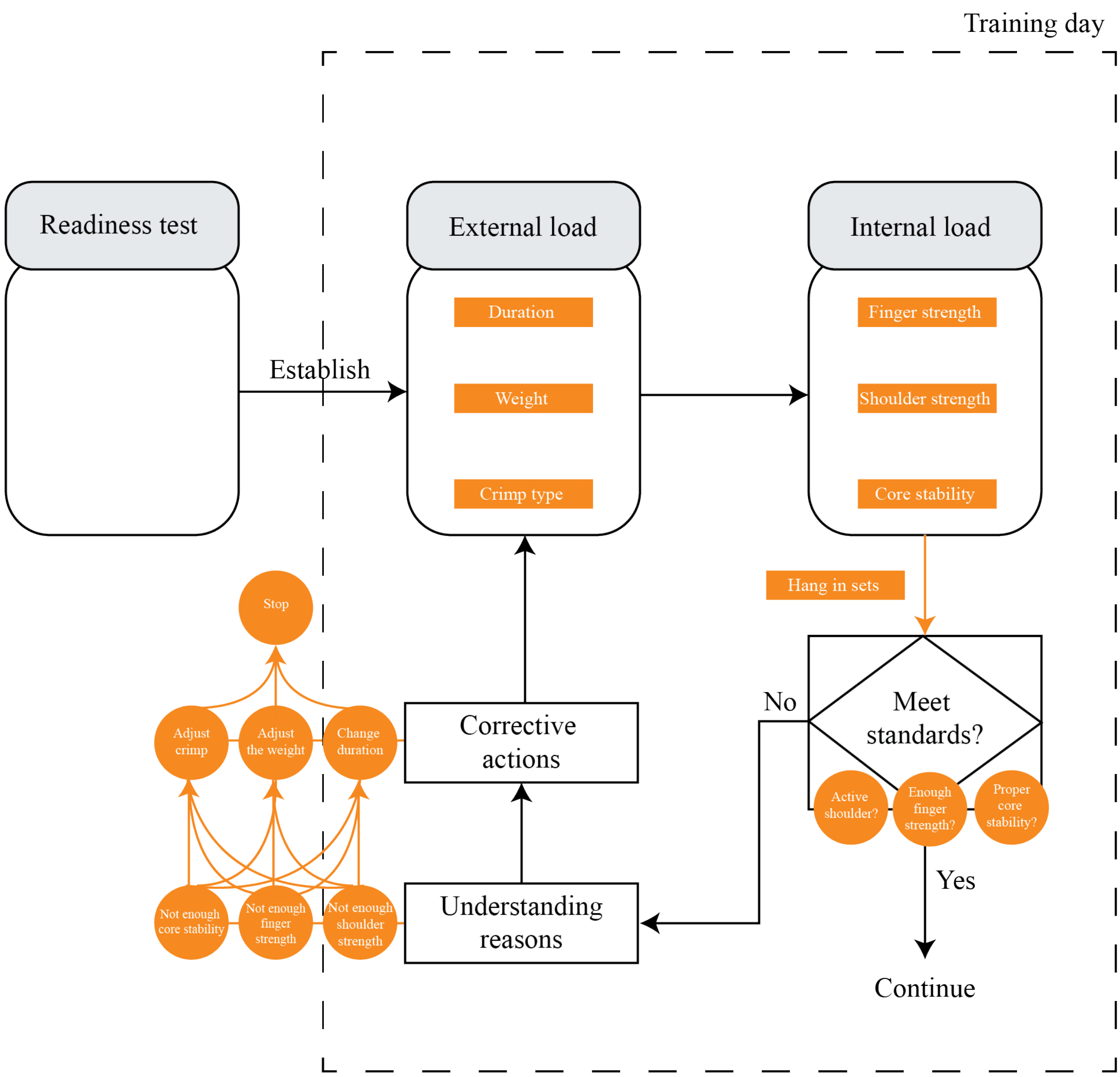


FIGURE 3.7: The proposed framework of figure 2.12 filled in for the training objective of hang in sets.

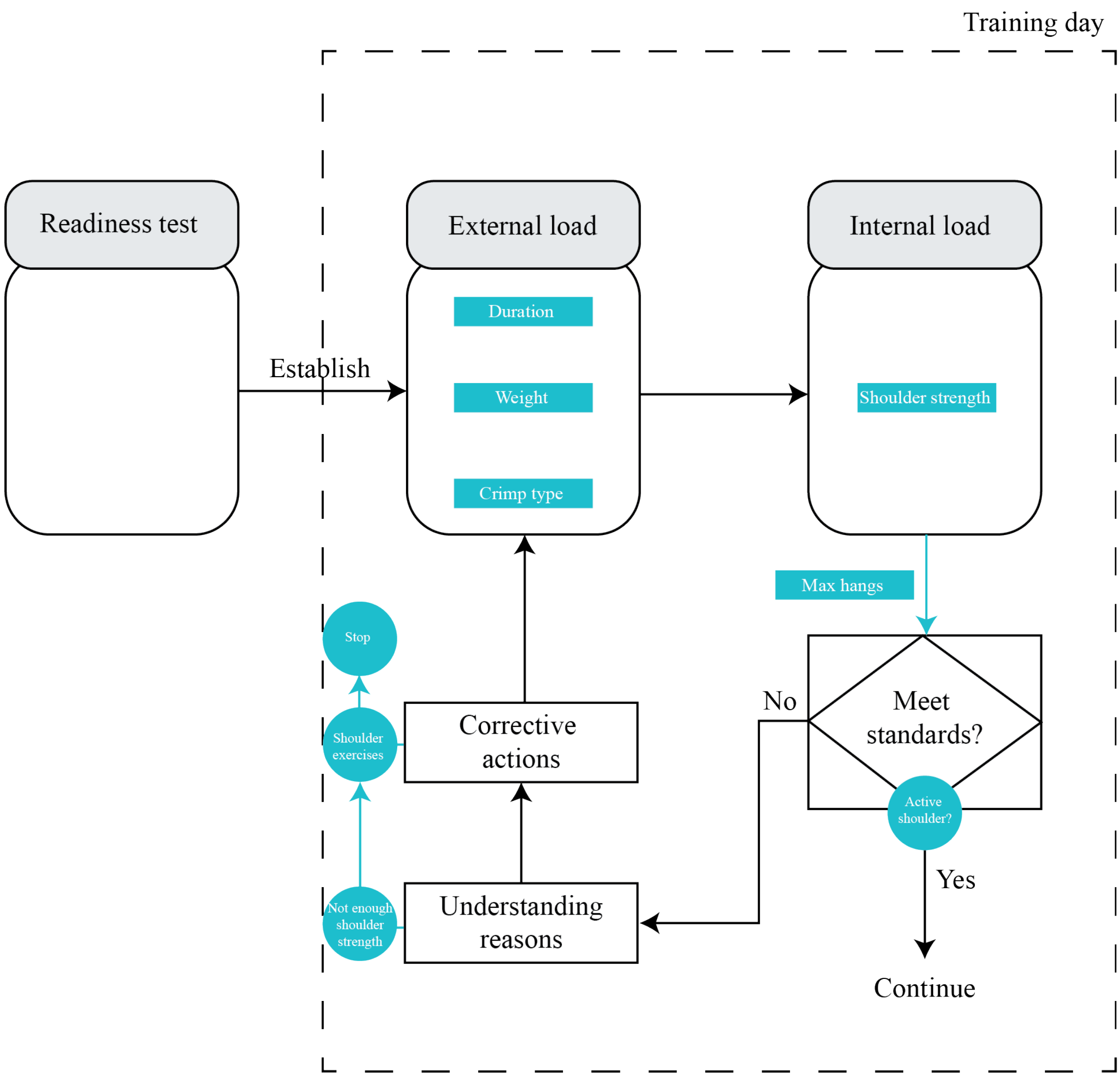


FIGURE 3.8: The proposed framework of figure 2.12 filled in for the training objective of max hangs.

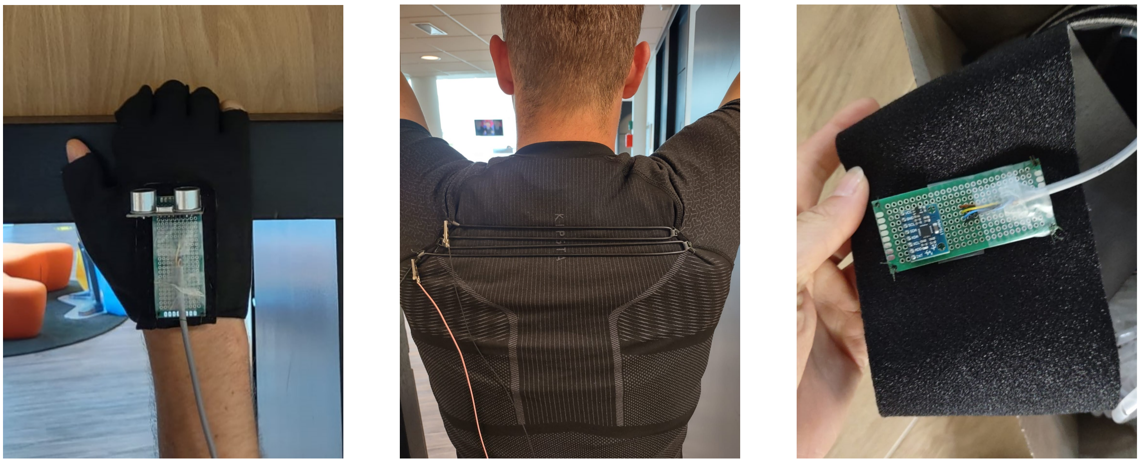
3.2 Phase II: Investigating KPI sensing and user feedback

The KPIs and training objectives are found in the previous section, and the next step is to create a system that can sense the KPIs, determine a threshold for the KPIs and create a feedback system to communicate this to the user with the training objective in mind.

The three KPIs mentioned in the previous section will be the foundation of the feedback system designed for injury prevention. However, to design a system based on these inputs, the KPIs need to be converted into measurable quantities to monitor those during hangboard training. As visible in figure 3.6, each KPI behaves on its axis. The finger strength (FS) KPI behaves on the y-axis (vertical movement), the shoulder strength (SS) KPI behaves on the x-axis (horizontal movement) and the core strength (CS) KPI is a combination of both axis, which represents shaking. For each of the KPIs, a sensor should be chosen to measure their behaviour. It is crucial to keep in mind that this thesis is focused on the research of a design approach. Therefore this research is neither investigating sensors nor algorithms but investigates human-media-interaction. The micro-controller of the prototype is an Arduino, as this platform allows for rapid prototyping to investigate interaction possibilities. The three sensors that can independently sense the behaviour of the three KPIs are discussed below.

- *An ultrasonic sensor* measures the distance from the sensor to an object in front of it. This means that if the sensor is perpendicular to the hand, it can measure the distance to the ceiling. The hand will move on the vertical axis if the hangboarder slips away (lacks finger strength). The ultrasonic sensor reads from 2 cm to 400 cm with an accuracy of 0.3 cm, which is good for noticing the deviation of the finger strength KPI.
- *A stretch sensor* measures the capacitance of the sensor. Stretching the sensor causes both the area and thickness to change, and this deformation results in a measurable change in capacitance. The stretch sensor can be connected between the two shoulders of the hangboarder. The sensor will notice when the hangboarder sags his shoulder due to the capacitance change of the sensor. The sensor reads 180 Ohms difference per centimetre, which is good for noticing deviation in shoulder distance with millimetre precision.
- *An accelerometer* measures static and dynamic acceleration. Static acceleration is the constant force acting on a body, like gravity or friction. Dynamic acceleration forces are non-uniform, and the best example is vibration or shock. The accelerometer can be placed on the back to detect vibration in the back. Vibration on the back is an indicator of core strength; the more stable the hang, the more core control the hangboarder has. The accelerometer reads -2g to +2g with a sensitivity of 270mV/g. This means that the accelerometer is sensitive to noticing small vibrations in the athlete's core.

The three sensors mentioned above are connected via one Arduino. The ultrasonic sensor is sewed on a glove as visible in figure 3.9a, the stretch sensor is sewed in a t-shirt as visible in figure 3.9b and the accelerometer is sewed on a hip band as visible in figure 3.9c.



(A) Ultrasonic sensor (B) Stretch sensor (C) Accelerometer

FIGURE 3.9: The Ultrasonic sensor, stretch sensor and accelerometer integrated on a glove, t-shirt and hip band respectively.

At the start of a hangboard training, the standards for each sensor are calibrated via the instructions mentioned in figure 2.9. During the hangboard training, deviation from the standard is monitored to see how the KPIs behave. In hangboard training, there are no quantified thresholds (yet) that the hangboarders must comply with. The user's involvement in making these terms is usually considered as a vital mechanism to enhance system quality and ensure successful system implementation [9][27]. For this thesis, the user is involved in creating these thresholds via a 5-point Likert scale survey to measure the user's satisfaction. Besides this, the user is involved in a design workshop, where the possible feedback system design is discussed and further explored.

3.2.1 Methods

5-Point likert scale survey

A 5-point Likert scale survey is a survey that is evenly scaled from which the respondents choose the level of agreement or disagreement [29]. A 5-point Likert scale survey is easy to fill in for respondents as they do not have to overthink and do not have to write lots of lines in order to answer. As the survey title already states, the survey is made up of a 5-point rating scale ranging from one end to another, with a neutral point in the middle. For this thesis, the 5-point Likert scale survey determines how satisfied the respondents are with the posture displayed in the proposed image. Therefore, the 5-point Likert scale survey ranges from very unsatisfied (1) to very satisfied (5).

Design Workshop

A design workshop with users gives space for creative collaboration. A design workshop can be organised to discord and explore opportunities. Next to that, the workshop can help spark discussion among users and give insights into the user's desires [29]. The goal of the design workshop was to gain more insights into possible feedback systems for the KPI sensing system (ultra-sonic sensor on the hand, stretch sensor on the shoulders, accelerometer on the back), as visible in figure 3.9a, figure 3.9b and figure 3.9c.

3.2.2 Setup

A survey is held in the Cube in Enschede[6] to be able to set the KPI reference value. Hangboarders and hangboard trainers helped by stating their desired threshold during hangboard training. In total, 13 participants (aged 18-27 years) were willing to participate in the study. It is impossible to photograph a shaking effect of an hangboarder. Therefore, for this thesis, the core-strength KPI is more a quality indication rather than a fixed threshold. In which less shaking indicates more quality in core strength. For the finger strength and shoulder strength KPI, it is possible to create an image sequence of postures. Each participant was provided with one sequence of five images to evaluate the hand posture (FS KPI), and one sequence of five images to evaluate the shoulder posture (SS KPI). Each participant was only provided with images and did not know what sensor values were behind these. Data is collected via the use of a 5-scale satisfaction rating. The survey is randomised in blocks[7], so the images within the blocks (hands, shoulders) are randomised to prevent the user from getting biased. Figure 3.10, shows the images of the hand used for the survey, in which you can see the slipping away process of the fingers. Figure 3.11, shows the images of the shoulders used for the survey, which shows the sagging of the shoulders. Both blocks of images are in order of ascending deviation from the first image, which was unanimously chosen as the correct posture by the participants. For both blocks, the first image on the left equals zero deviation from the reference value. In contrast, the others in the hand sequence have a sensor value deviation of 1, 2, 3, or 4, respectively, and the other images in the shoulder sequence have a sensor value deviation of 30, 60, 90, or 130, respectively.

FIGURE 3.10: Images of the survey block to determine the FS KPI threshold, in order of ascending deviation.

[6]https://cubebouldergym.nl/
[7]https://www.idsurvey.com/en/randomization-increasing-data-quality-in-research/

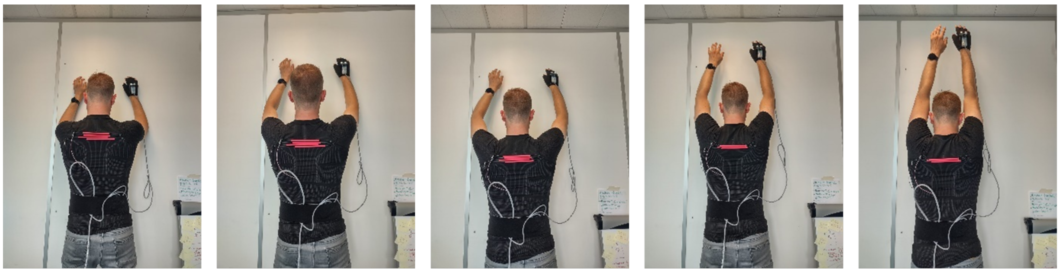


FIGURE 3.11: Images of the survey block to determine the SS KPI threshold, in order of ascending deviation.

The design workshop was conducted with five participants who had background knowledge on creating User Experiences, hangboard training or both, as visible in figure 3.12.

Participant	User Experience designer	Hangboarder
1	V	X
2	V	X
3	X	V
4	X	V
5	V	V

FIGURE 3.12: Background knowledge of the participants who participanted in the design workshop.

The workshop started with an ice-breaker exercise called 30-circles[8], in which the participants had 3 minutes to fill 30 circles. This warming-up exercise aims to spark the participants' creativity in a brief period. After the warming-up exercise, the three KPIs and the three sensors are explained to the participants. After this introduction of 10 minutes, the participants are asked to help tinker a fitting feedback system based on the output of the sensors. A user journey template[9] is used to structure the workshop and help the participants work to the workshop's end goal: a full user-journey map, with the translation to a feedback design. During the workshop, one facilitator kept an eye on the participants and answered questions when those were raised. The workshop lasted 90 minutes in total.

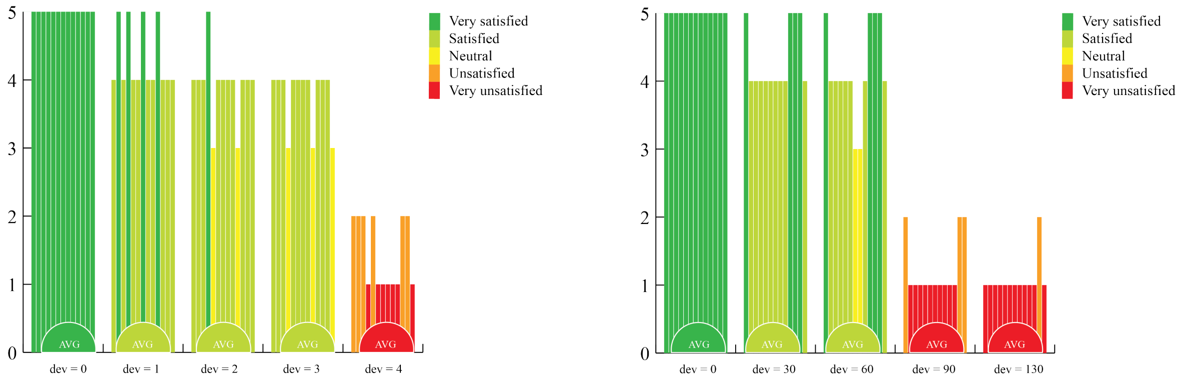
3.2.3 Results

KPI Threshold

The participants were asked to rate every image with a rating from 1 (very unsatisfied) to 5 (very satisfied), according to how satisfied they feel about the posture in the image. The results of the survey can be seen in figure 3.15 and 3.16. In both graphs, it is visible when there is a drop in satisfaction among the users. From the user's perspective, the drop in satisfaction is when a system should step in and warn the user. The FS KPI should not deviate more than 3; the SS KPI should not deviate more than 60. Besides setting the threshold for a user warning in the KPI monitoring tool, it would be helpful to have a grey zone in which the system lets the user know

[8]https://www.ideo.com/blog/build-your-creative-confidence-thirty-circles-exercise
[9]https://miro.com/templates/customer-journey-map/

he is coming close to getting a warning signal. In this grey zone, it is for the user still possible to improve his posture (if possible) without getting the final warning signal.



(A) Threshold FS KPI (B) Threshold SS KPI

FIGURE 3.13: Results of the survey in a graph, threshold for finger strength KPI and shoulder strength KPI.

Feedback Design

The result of the design workshop is a filled-in User Journey template as visible in figure 3.14. The participants were asked to think about the given four topics in the user journey: the user's desires, the feedback possibilities, goals and the difficulties the user faces. The participants elaborated on these topics in the four phases they came up with. The four phases of the design workshop are: before the training, the hang during the training, the rest moments during the training, and after the training. The insights from the design workshop can be used to develop a feedback design system.

Based on the participant's feedback, it is suggested to work with visual and auditory feedback to communicate the hangboard process to the user. Deviation in sound can help the user to understand the relationship between what he *feels* and how he should *act* accordingly. For example, an increasing sound can help the user to understand an increasing risk of overloading. The most important aspects of a system in hangboard training are: instruction to start the training correctly, a timer to know how long the training takes, a graph that resembles the athlete's performance, a sound that resembles the athlete's performance, tips to adjust the training.

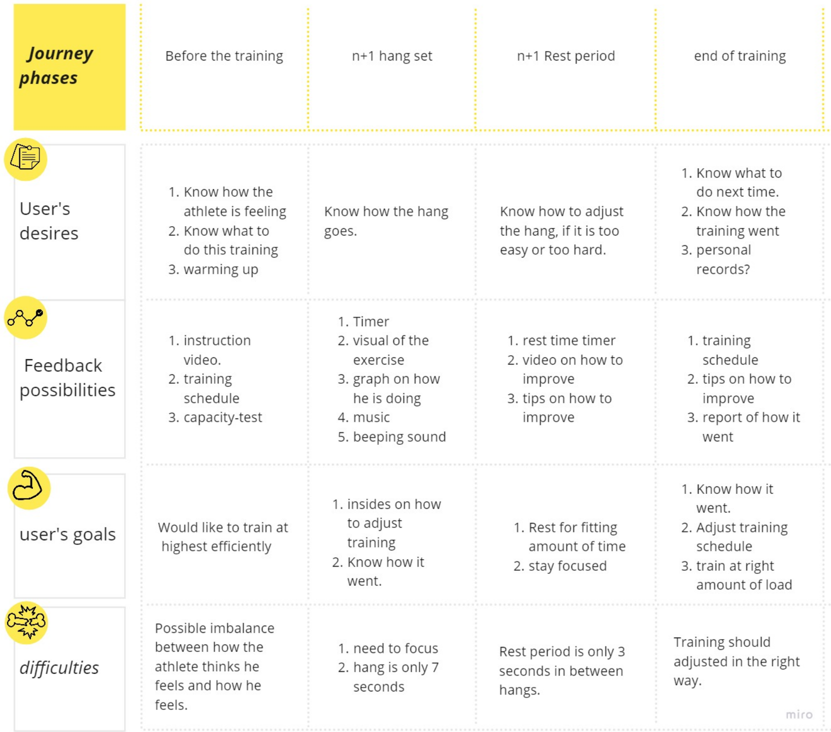


FIGURE 3.14: Results of the design workshop: User Journey

3.2.4 Conclusion

KPI threshold

The results of figure 3.15 and figure 3.16 can be merged into a feedback recommendation for a system that reacts the same as hangboarders and trainers. Of course, it has to be taken into account that this threshold has not been researched in dept and can be improved with future work. However, for this KPI monitoring tool, it is key to set the deviation threshold to give feedback with at least the feedback level of hangboard experts. Figure 3.15 and figure 3.16 show the feedback recommendation for a potential system for hangboard training.

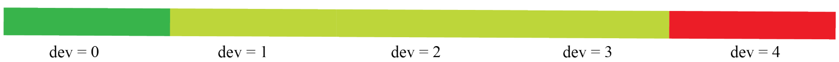


FIGURE 3.15: Feedback recommendation for the deviation threshold of the FS KPI, based on the results of the survey.

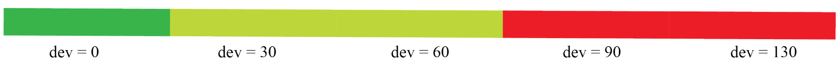


FIGURE 3.16: Feedback recommendation for the deviation threshold of the SS KPI, based on the results of the survey.

Feedback system

From the results of the design workshop, a feedback framework consisting of three phases can be concluded as visible in Figure 3.17.

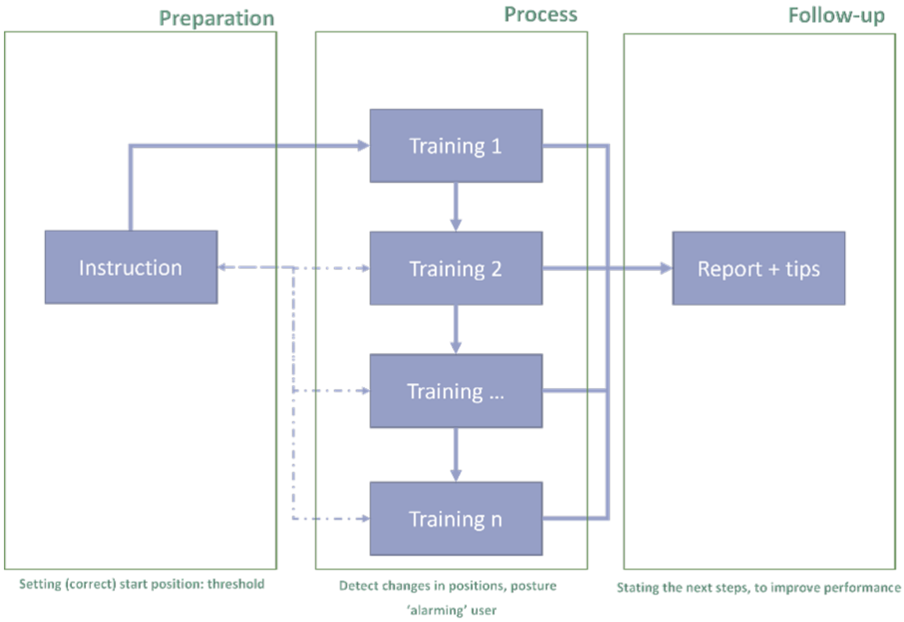


FIGURE 3.17: Feedback system for hangboard training.

(1) The preparation phase. From the user, it became clear that the hanging posture should be correct to execute the exercises properly. However, the correct posture is different per person and cannot be based on certain fixed numbers due to different body sizes. This project does not dive further into creating an algorithmic model in which the correct posture is calculated based on body measurements but uses instructions to help the athlete find the correct posture.
(2) The process phase. During this phase, the user would like to maintain the correct posture from the previous phase and would like to be alarmed when deviation from the correct posture occurs. Besides this, the slippage of the hands and the sagging of the shoulders can be corrected by the user when it is notified on time (until a certain level of deviation). While the core strength indicator on the back is an indicator of stability and is less likely to be corrected by the athlete and indicates the quality of the hang.
(3) The follow-up phase. The user desires to get a report after the training, to see the training results and to get some follow-up steps along with the user's goal to improve his performance. As the detection system can detect which link is the weakest (hands, shoulders or core stability), it is possible to provide the user tips on this specific weak link. Understanding the weakest link of the athlete offers the opportunity to use focused training on the athlete's weakness. As the athlete's maximum performance equals the weakest link's maximum performance, the performance of the hangboarder will improve when the weakest link does. After the athlete has improved his weakest link, another link will become the weakest and this link can again be improved via focused training.

3.3 Phase III: User test

After phase I, the KPIs and training objectives for hangboard training are found. Later in phase II, a system is created that could sense those KPIs. Then, a feedback system was created along the threshold, which was set with the help of hangboard experts. The next step is to combine the feedback design and the KPI sensing system in a prototype tested in an experimental user study.

3.3.1 Methods

Within-Subjects Study Design

The goal of the user test is to investigate whether the designed system can provide meaningful feedback on the training schedule and training load of the user. The system is developed to give the users more insights into their internal load to better adjust the external load to train at the desired training load. The system provides insights into the user's internal load and gives tips for adjusting the external load. A within-subject study design will be done with two groups. A within-subjects design is a user study that compares two groups of participants with the same treatments to test the independent variable [29]. For this user test, treatment A is 3 sets of hangboard training with feedback and treatment B is 3 sets of hangboard training without feedback, to test the dependent variable: performance, the hang time of the hangboard athlete in correct posture. Besides, an in-depth analysis of the results of the user study helps to understand how users react to the provided feedback when they surpass the system's threshold. The most significant advantage of a within-subjects design is that you need only half of the participants that you would need with a between-subjects design. Next to this, as all participants get the same treatments, it is less likely that individual differences make errors in the data [25]. From the previous sections, it has been stated multiple times that individual characteristics play an essential role in hangboard training, so reducing errors associated with individual differences is important. One major disadvantage of a within-subjects design which is important to mention is the carryover effect [29][25]. The carryover effect refers to the influence of having one treatment before another treatment on the user's behaviour and performance during the second treatment.

3.3.2 Setup

In total, 12 participants were willing to participate in the experimental study, where the impact of the system's feedback on the hangboarder's KPIs during hangboard training was tested. The user test took place in the Cube in Enschede. The participants were divided over two groups for a counter-balanced research design. All participants had to perform 6 sets of 6 repetitions of a 7 sec hang with self-chosen grip size and additional weight, with 3 seconds rest between the repetitions and a 1-minute rest between the sets. Group A received the system's feedback during the first 3 sets, and group B received the system's feedback during the last 3 sets, while the sensors were on the body for all 6 sets. It is chosen to use the training objective of hang in sets during the user study, as the max hang cannot be performed too often by the hangboarder due to the high training intensity.

The prototype the user tried out consisted of three phases: preparation, training, and follow-up. For the first phase, the preparation, instructions (from section 2.1.5, figure 2.9) on how to hang with active shoulders is spoken out loud by the facilitator of the user study. The athlete's posture is then checked by a trainer who was present in the climbing hall to decrease the possibility that the athlete gets hurt by an incorrect start posture. After the athlete has found the correct posture, it is time to start the training. The athlete is asked to wear the glove (finger strength KPI), t-shirt (shoulder strength KPI) and the hip band (back strength KPI), as visualised in figure 3.18.

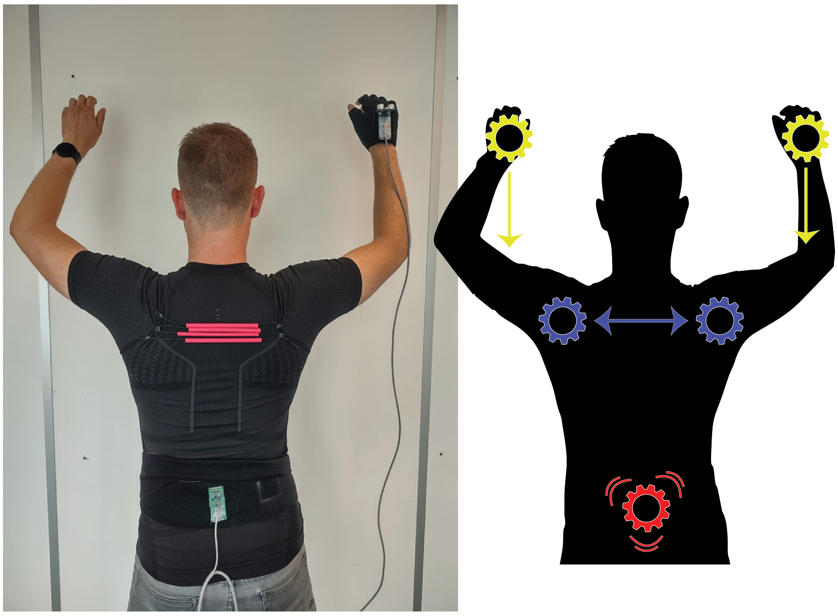
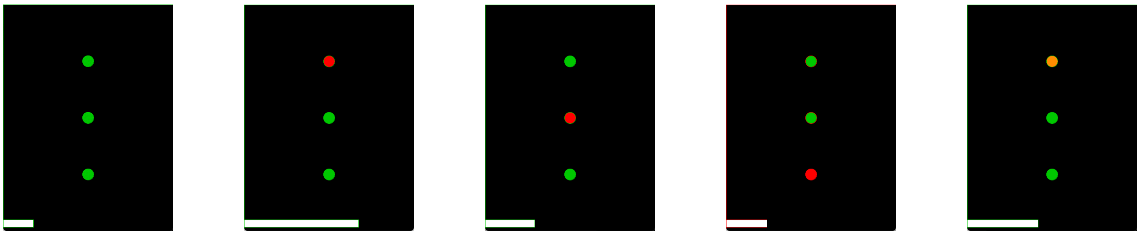


FIGURE 3.18: The KPI sensing system figure ?? integrated in a glove, t-shirt and hip band, worn by a test person.

During the training (training phase) the athlete receives feedback on the three KPIs (hand, shoulder and back) as visible in figure 3.19 and via audio feedback (more details about the audio-design will be discussed below). As visible in figure 3.19a, the athlete's posture is good, and the challenge is to keep all these circles green for the remaining time (visualised with a white bar at the bottom of the screen). If a circle turns red, the corresponding KPI deviates from the standard value. Each KPI has its circle on the screen, with the finger strength KPI (figure 3.19b, shoulder strength KPI (figure 3.19c), and the core strength KPI (figure 3.19d). Besides red circles which indicate a warning signal, orange circles indicate a warning zone, where it is still possible for the user to improve his posture before the circles turn red.

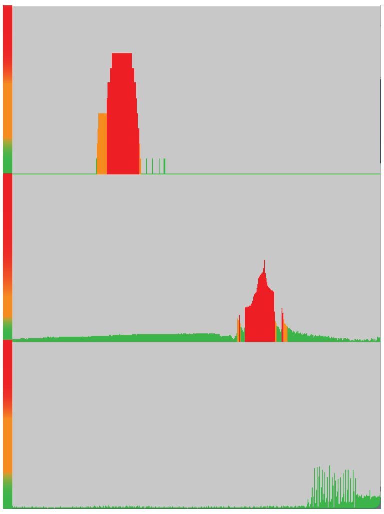


(A) (B) (C) (D) (E)

FIGURE 3.19: Examples of possible feedback that can be given by the system.

The transition from green to red is also provided to the user via a tone. The tone frequency gets higher as the athlete's performance deteriorates. The addition of sonification to visual feedback enhances complex motor task learning [39]. Auditory feedback based on sensor data can help the athlete during his self-assessment by providing direct information on the performed movements [10]. When the athlete understands his/her performed movement, repeating the movement will be easier and the movement repeatability of the athlete will increase [23] [40]. Next, the auditory modality remains largely available without interfering with other modalities and can be processed rapidly [10]. Based on the user's feedback, auditory feedback is combined with visual feedback so that the user can easily see which KPI is lacking.

After the training (follow-up phase), a report is created and provided to the athlete. The report shows the athlete the behaviour of his three KPIs during the training, with graphs, as visible in figure 3.20a. The coloured peaks indicate where the athlete exceeded the thresholds and thus where he can improve. Based on the report, tips are given to the athlete based on the behaviour of the KPIs to ensure the thresholds are less exceeded and the athlete is less prone to get overloaded and injured. The tips corresponding to the behaviour of the KPI are visible in figure 3.20b.



(A) Report

KPI	Tips
Finger strength KPI	- Change crimp size - Change the weight
Shoulder strength KPI	- Change duration - Shoulder exercises
Core strength KPI	- Change the weight - Change the duration

(B) Tips

FIGURE 3.20: Report (a) on the behaviour of the finger strength KPI, shoulder strength KPI and the core strength KPI, respectively. The tips (b) given by the system based on the behaviour of the three KPIs.

The participants were asked to hang for 6 sets, with 6 repetitions of 7 seconds per set. It is essential in the experimental research study that the athlete starts at his own training level because when the exercise is too easy for the athlete, it is assumed he can execute the exercise without any problems, which means: no feedback is given by the system. The experimental research study investigates the influence of feedback during hangboard training. Therefore, the participants are asked to choose the external loads (additional weight and grip size) for the training based on their training level, to ensure the athlete starts at a reasonable level. During the test, the athlete's hang time in the correct posture (green zone) is timed per repetition and averaged per set. After testing the prototype, the participants were interviewed via a semi-structured interview as explained in section 3.1.1.

3.3.3 Results

Quantitative results

The previous section explained the setup of the user test and as mentioned, the hang time in which the athlete hangs with good posture (green zone) is timed and noted. All 12 participants executed 6 sets of 6 repetitions, in which group A got the system's feedback during the first three sets, and group B got the system's feedback during the last three sets. This means that the athlete's performance while receiving feedback (hang time in correct posture) can be compared with the athlete's performance while not receiving the system's feedback. An interesting observation is important to mention; none of the participants received a red circle during the repetitions. This means the participants carried out the exercises within the green and orange zones, both injury-safe zones according to the threshold research in section 3.2.3.

Figure 3.21 shows the mean and standard deviation plot for performance per participant over the six sets. The error bars provide details on the variances in data. As visible in the figure, the error bar of participant 8 (SD = 12,433) is the biggest, which indicates that the data points (athlete's performance per set) are more spread out. The data points of participants 5 (SD = 2,500) and 12 (SD = 2,924) are more clustered around the mean and are therefore more reliable than participant 8. From figure 3.21 it also becomes clear that the performance means of participants 7 and 8 are lower than the other participants' performance means.

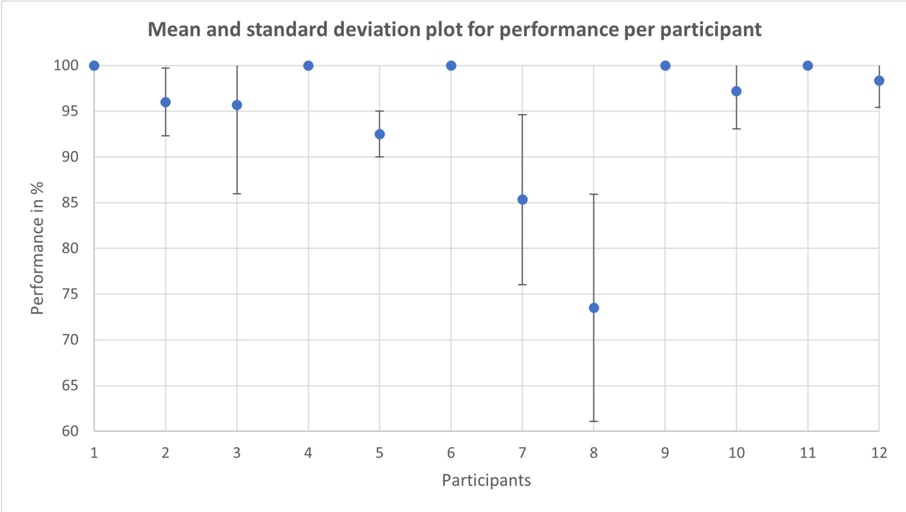


FIGURE 3.21: Mean and standard deviation plot for performance per participant.

However, in the case of this user test, a lower performance percentage does not automatically mean that the participant was a less skilled hangboard athlete. The athlete's performance during the user tests highly depended on the external loads that the participant chose himself. So, while looking at the results, it has to be taken into account that the performance level does not refer to the athlete's skill level but refers to the athlete's performance level while training with specific external loads. All participants chose body weight as the external load and had different choices on grip size (19mm and 25mm) and crimp type (open hand and half crimp), as can be seen in figure 3.22. According to the interviews from section 2.1.2, hangboard training with an open hand and a 25 mm grip size are less demanding than climbing with a half crimp on a 19 mm grip size. Therefore, it can be concluded that participants 5 and 8 chose the most demanding external loads for the training during the user test. For participant 8, these external loads were too demanding, as can be concluded from his performance and the data variance among the sets. Participant 5 had a performance level of 92.5% and a standard deviation of 2.5, with which it can be argued that participant 5 chose fitting external loads for his training while participant 8 did not.

From the standard deviation in figure 3.21 it can be concluded that each user has different needs in terms of feedback. For example, participant 8, has a more significant error marge than participant 2. Therefore, the bandwidth in which feedback is given can be smaller for participant 2 than for participant 8, in order to provide the same feedback frequency for both participants. Adjusting the bandwidth of the feedback system based on the standard deviation can help the system to become effective for all skill levels. This also applies to the threshold of the system. A more expert hangboard athlete needs a more precise threshold than a beginner athlete, as an expert has minor errors to tweak which require more critical feedback.

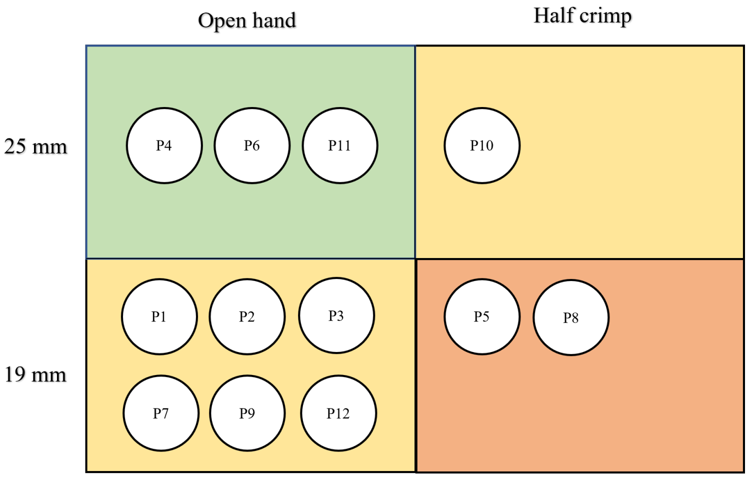
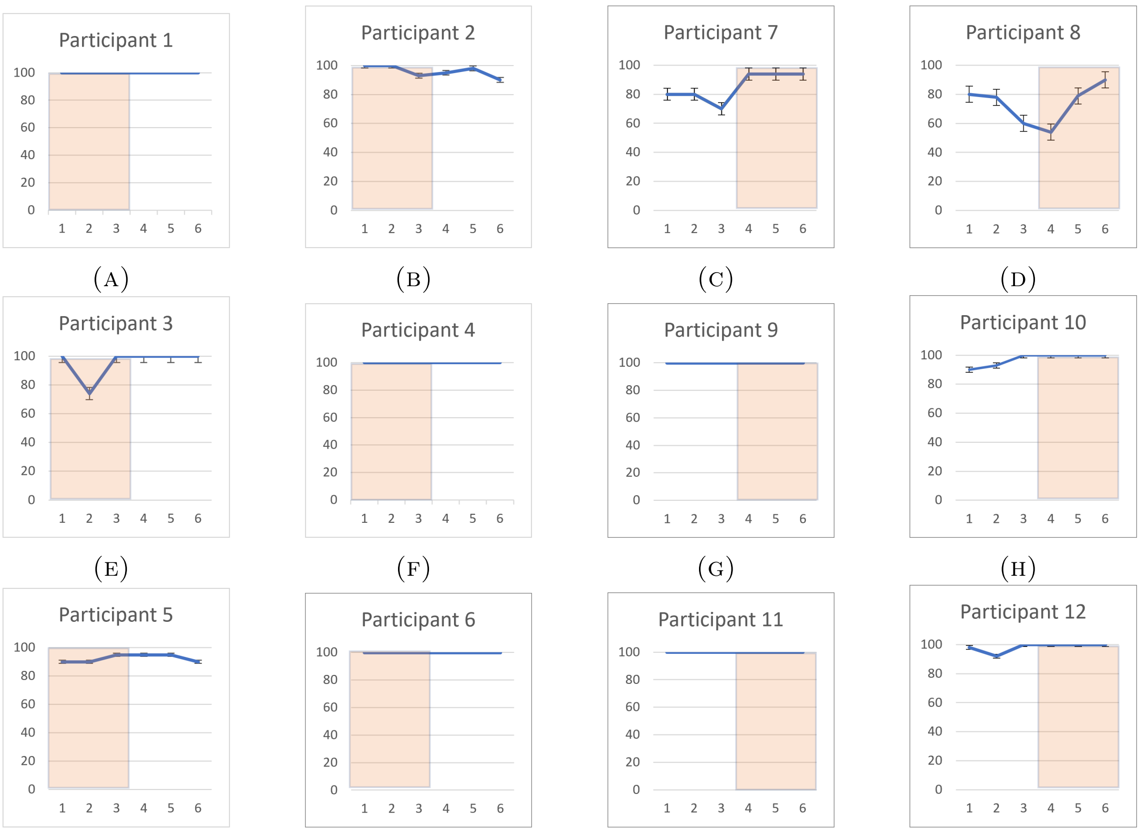


FIGURE 3.22: Mapping of the external loads chosen by the participants. Grip size *19 mm* or *25 mm*, crimp type *Open hand* or *Half crimp*

To dive deeper into the performance of each participant, the average performance per set per participant is plotted in figure 3.23a till figure 3.23l. These figures show the individual measurements of the 12 participants who participated in the user study.



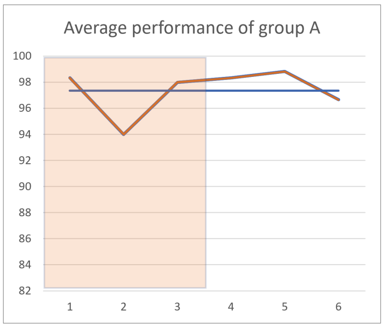
(A) (B) (C) (D)

(E) (F) (G) (H)

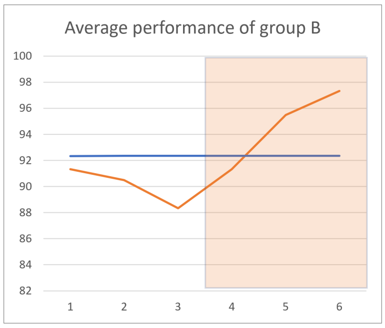
(I) (J) (K) (L)

FIGURE 3.23: % hang time in good posture over 6 sets of 6 repetitions, where the participant received the system's feedback during the coloured zone.

The coloured zone in the graph resembles the time when the participants received the system's feedback. The vertical axis represents the % of seconds the hangboarder hangs in the correct posture. If the athlete performs at 100%, he hangs in the correct posture for that specific set. Besides, performing at 100% means that the participant did not receive feedback other than green circles throughout the whole set. As visible in figure 3.23, there were five participants, figure 3.23a, 3.23f, 3.23j, 3.23g, 3.23k, who only saw green circles in the feedback system, as they performed 100% of the time in good posture. This can either be because (1) the hangboarder is performing really well during the 6 sets, (2) the external loads chosen by the participant were not challenging his internal loads or (3) the threshold was not sensitive enough. Participant 3 (figure 3.23e) and participant 5 (figure 3.23i) performed better after receiving the system's feedback, as they positively improved their posture during the feedback zone. In contrast, participant 2 (figure 3.23b) had an overall decrease in performance which could also be because of tiredness or too difficult external loads. Participant 7 (figure 3.23c) and participant 8 (3.23d) both show an increase in performance after receiving the system's feedback. However, even though they seem to perform better with the feedback, they do not reach a 100% level in any set. Participant 10 (figure 3.23h) and participant 12 (figure 3.23l) seemed to have some difficulties with the first three sets and then reached a correct posture and kept that posture for the rest of the sets. Both participants 10 and 12 fell in participant group B, and thus, they improved their posture without the help of the feedback system, as that was not yet active on the moment of improvement. Besides looking at the individuals, it is interesting to look at the average performance of both groups, as visible in figure 3.24.



(A)

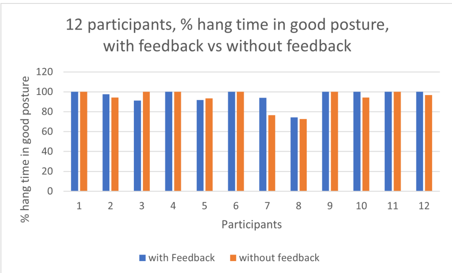


(B)

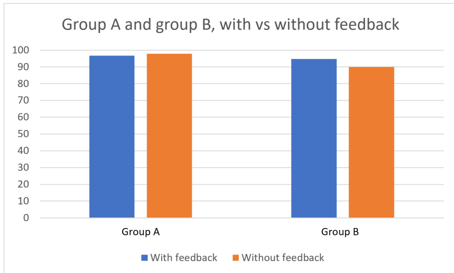
FIGURE 3.24: The average performance of group A and group B per set, visualised with a red line, and the total average performance over all six sets, visualised with a blue line.

From figure 3.24 it can be seen that group A (M = 97,35%) had an overall higher performance than the participants from group B (M = 92,36%). The figure shows that Group A's performance dropped in set 2 and was improved while receiving the system's feedback in set 3. In the three last sets, it is visible that the participants' performance had an overall drop. The performance of group B seems to improve while receiving the system's feedback. Group A received the feedback for the first three sets and then had to finish the total of 6 sets without feedback. This could have led to demotivating during the last three sets. Group B started the training with 3 sets without feedback and finished the 6 sets with feedback during the last three sets; this could have led to more motivation during the last three sets. The carry-over effect, as mentioned earlier, is essential to consider while looking at the results.

As visible in figure 3.25, some individuals benefit from the feedback given by the system. Especially those who have relatively a lower performance seem to benefit more from the feedback than those who already perform close to 100%. However, this can be explained by the plateau of the maximum performance, as it is harder to improve a performance close to perfect than a performance with more room for improvement. In total, two participants do not seem to benefit from the feedback (participants 3 and 5), five participants already performed at a 100% level (participants 1, 4, 6, 9 and 11), and five participants (participants 2, 7, 8, 10, and 12) did benefit from the feedback during the training (see figure 3.25a). However, of these five participants who benefits from the feedback, was only one participant in group A and the other four were in group B. Both participants who did not seem to benefit from the feedback were located in group A. This can also be seen in figure 3.25b, as it is visible that the feedback did make a difference in performance in group B, even though in group A there is a slightly better performance for the hangboard training without feedback. However, it has to be kept in mind that two of the six participants of that group did not benefit from the feedback, and three of the six participants performed at 100% performance.



(A) Individual level



(B) Group level

FIGURE 3.25: The impact of feedback on the hangboarder's performance, on individual and group level.

The last interesting insight from the data was the most common weakest link among the participants. The system measures the three KPIs independently, and therefore it was possible to look back at the data and count the most common weakest link. From every participant, the KPI with the highest error rate over the 6 sets was chosen as the weakest link. As visible in figure 3.26, the shoulder strength KPI had the most counts among the participants, only Three participants had the finger strength KPI as the weakest link.

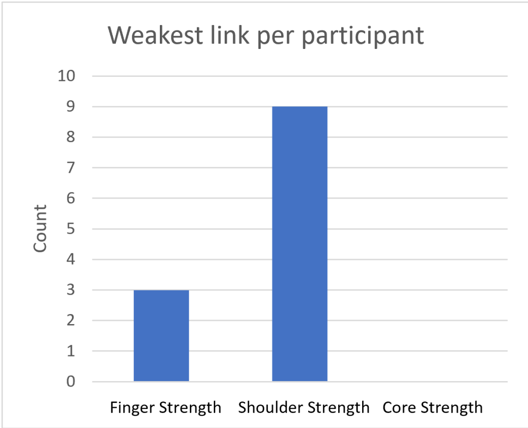


FIGURE 3.26: The participant distribution for the experimental user study.

A statistical T-test is done to determine if there is a significant difference between the means of performance during hangboard training with feedback compared to hangboard training without feedback. An F-test is used to determine whether the variances are equal or unequal. Since the p-value is larger than 0.05, we fail to reject the null hypothesis and conclude that there is no difference in the variance of performance level between hangboard training with feedback and hangboard training without feedback. As the p-value is insignificant, it is assumed that the variance is equal in a T-test. The T-test hypothesis is shown below in equation 3.1.

$$H_0 : \mu_1 = \mu_2 \qquad\qquad H_1 : \mu_1 \neq \mu_2 \tag{3.1}$$

The p-value for two-tailed t-tests is insignificant ($p = 0.621$). Therefore, the difference between the means is not statistically significant. Therefore, there is no statistical proof that training with feedback significantly influences the performance of the athlete compared to training without feedback.

Qualitative results

The interview brought a lot of new valuable insights to light. After the hangboard training, the participants participated in a semi-structured interview. Different topics can sort the feedback from the user.

First topic: **Insightfulness**. From the participants, it came forward that the feedback helped to gain more insights into their hang behaviour. The participants state that it can be frustrating to fall off the hangboard without knowing the cause. The system can help the participants by understanding the cause and giving tips to improve. From the answers given by the participants, it became clear that the system creates more awareness in the user about their behaviour during hangboard training. Besides, participants claimed that they think that they would feel more motivated to improve hangboard training if they knew what KPI is the weakest and how to improve this.

Second Topic: **Implementation**. Each participant seemed quite enthusiastic with the system after the training. A few participants stated that they like that hangboard training is more often researched and has gotten more scientific attention now that climbing has become an Olympic sport. With this enthusiasm, different implementation possibilities were ideated by the participants.

- A few participants mentioned that active shoulders is one of the most important aspects of hangboard training. The active shoulders also seem to be an essential part of bouldering and wall climbing. Currently, active shoulders are subjectively evaluated by a trainer who is present. However, when there are more athletes in one training, it is hard to keep track of each athlete's shoulders. Therefore one idea is to use the t-shirt of the system with the shoulder strength KPI to detect if the athlete has active shoulders or is sagging. This can, for example, be indicated on the t-shirt with a LED strip. This idea also came forward from other participants who thought about athletes who had just started climbing. In training for beginners, the t-shirts of the athletes are sometimes taped to let the athletes feel if their shoulders are sagging (tape is bending). This is the same principle as with the shoulder strength KPI; however, in the system of this thesis, the tape is a stretch sensor.
- The use of phones is accepted by the hangboard community, and in a climbing hall, there is often a small edge where a phone can be placed on. Via that statement, the discussion led to integrating this thesis's system in an existing app such as CrimpD[10]. In that case, the system is the input for the decision-making in the app to create training schedules and feedback. Currently, the athlete's performance has to be filled in manually by the athlete, including the bias of the athlete (how can he fill in his performance if he does not know how he performed?). The system from this thesis offers the opportunity to have a quantified value that can be used to create a training schedule grounded in measurements.
- From the interview, it came forward that a readiness test can help determine the participants' internal loads on that specific day. Then, it is easier for the user to start the training with fitting external loads. Next, when the user starts with fitting external loads, it is likely that at least the first part of the training can be performed on a 100% level before adjustments are needed (if needed at all). According to the participants, the system used in the user test has the potential to be the measurement system of the readiness test. One participant mentioned that, for example, speed climbers can only start their training if they perform a speed climb within at least 80% of the time of their high score. If the athlete cannot perform at that level, he is not feeling good enough for training, and he is sent home. This 80% principle might be worth looking into for hangboard training when a sensor system can provide the needed quantified measures.
- From the discussion on the readiness test, it also came forward that the system could help test the athlete and decide on what level he is on or should climb on. The climbing level of an athlete is an important characteristic that resembles the athlete's climbing skills. This climbing level is based on the level of the most complicated route the athlete can climb. However, as climbing a route involves more than just strength, it would be helpful to have a hangboard level as well,

[10] https://www.crimpd.com/

which can explain the strength level of an athlete. This strength level can be measured by this thesis's system, which is thus another potential.

- It is stated by the participants that you start to train with your body weight on an hangboard if you can execute the scapular pull-up[11] correctly. According to the participants, the judgement of executing the exercise correctly is subjective and hard to grasp for the athletes. Therefore, a situation in which the athlete is waiting on the 'go' from the trainer often arises. In that situation, it is hard for the athlete to receive a 'no go' while the trainer cannot ground his 'no go' in any measurements. The thesis's system can help ground the trainer's opinion in measurements to give the participants the feeling of unbiased training advice.

3.3.4 Conclusion

From the quantitative results, it can statically not be concluded that the feedback affects the user. Visually, there is a slight improvement in performance in group B, where the feedback is provided in the last three of the six sets. In group A, there is a slight difference in performance, where the performance was better when no feedback was provided to the user. Next to this, in group A, there was only one participant who benefited from the feedback, the other three participants were neutral, and two participants did not benefit from the feedback. Therefore, this difference should be further tested in future work. In group B, a positive effect on performance due to the feedback given is visible. However, as both groups consist of six participants, it is wise to redo the experiment with more participants or as a between-subject design, to find a statistically significant quantitative difference.

From the qualitative results, it can be concluded that the participants' self-perception increased by providing feedback during training. The participants were more aware of what KPI was the weakest and were eager to improve this KPI as the way to improvement became clear to them via the provided report. Besides, five implementation potentials came forward: (1) Further developing the t-shirt with the stretch sensor to measure the activity of the shoulders, (2) integrating the system with existing hangboard apps, (3) using the system to develop a readiness test, (4) using the system to determine the climbing level of the athlete, and (5) using the system to ground the opinion of the trainer in measurements.

In conclusion, a training load management system to prevent injuries is received well among hangboard athletes. The feedback cycle used for this management system is crucial in its effectiveness and application to hangboard training. Therefore, the used feedback cycle can be seen in the figure 3.27 below.

[11] https://trainingforclimbing.com/the-best-exercise-youre-not-doing-the-scapular-pull-up/

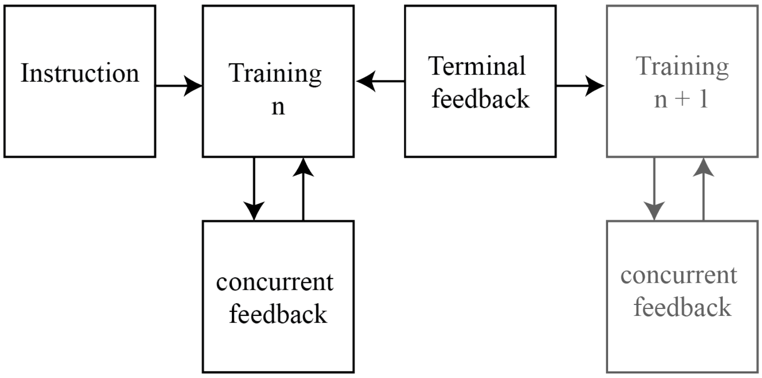


Figure 3.27: Structure of the feedback cycle. The figure is based on the figure in the *A Design Space of Sports Interaction Technology* Reader [34].

Chapter 4

Conclusion and Discussion

This thesis was a follow-up case study with a focus on hangboard training to investigate the process of designing interactive injury prevention applications. Throughout this research three research questions have been answered:

- **How can the internal load capacity of hangboard athletes be quantified and effectively communicated to the user?** The internal load capacity of the hangboard athletes were quantified for this research via the FS KPI, SS KPI and the CS KPI. By setting the desired thresholds for these three KPIs, it was possible to communicate the internal load bandwidth in which the hangboard athlete should train to reach the desired training outcome.
- **How can the external load of the athlete be tuned on the internal load of the athlete during hangboard training?** The created prototype is capable of tracking the deviation per KPI during a hangboard training. Feedback can be given based on the deviation from the sensor's start value (correct posture). As mentioned earlier, the total endurance of the athlete equals the weakest KPI of the athlete. Therefore, it is possible to understand the athlete's internal load (the KPI with the highest deviation), adjust the training accordingly (tune the external training loads) to reach the desired training outcome.
- **How can interactive feedback benefit the self-perception of the athlete's training load during hangboard training?** An usability test is executed as last step of this thesis, in which the impact of the feedback on the performance of the athlete was investigated. From this test, no significant difference was found. However, from the qualitative results it became clear that the users were more insightful about their own training due to the provided feedback of the system.

In order to answer these questions, information from literature, interviews, and observations were collected. The collected information was used to get a first idea of the hangboard training scenario, in which three user problems came to light. First, it is hard for hangboarders (especially for beginners) to find the right external loads so that they do work out but do not overload. Second, it is hard for the hangboard athletes to evaluate and correct the right (active) posture. Third, it is hard to grasp for hangboarders when to let go of the grip at the moment that their internal loads and external loads start to imbalance to prevent overloading.

With the user problems in mind related work was investigated and discussed. Based on the state of the art of interactive injury prevention applications for hangboard training, a framework was proposed. The proposed framework helped to map the necessary components before it was possible to design an interactive application that fits hangboard training. The value of these components was found via two phases of co-design in which surveys and interviews were held and lo-fi prototypes were created, tested and evaluated. The components from the framework are visible in the first column of figure 4.1, and the value of the components for hangboard training are visible in the second column of figure 4.1.

Components	Hangboard training
Internal load indicators	FS KPI, SS KPI, CS KPI
Internal load standards	Dev FS ≤ 3, Dev SS ≤ 60, Dev CS = quality
External load indicators	Duration, weight, repetitions, crimp type, grip type
Failure reasons	Dev FS > 3, Dev SS > 60, fall off the hangboard
Corrective actions	Change duration, weight, weight, repetitions, crimp type, grip size, or stop.

FIGURE 4.1: The components of the proposed framework applied to hangboard training.

After the components were found, the third phase of co-design was executed, in which a final prototype was user tested via a within-subject design. From the user test, qualitatively, there was an effect found on the user's awareness and an increase in the level of depth of the user's self-evaluation after the hangboard training. Quantitatively, there was no statistically significant difference found between the performance of the athletes with and without the system's feedback. However, there seemed to be some positive effects on the user's performance while receiving the system's feedback, however as this was not statistically proven, it should be further investigated before any concrete conclusions can be drawn.

4.1 Contributions

This thesis has many findings, and these are discussed throughout this report. However, there are three significant contributions which are worth mentioning again.

First, the created system provides real-time feedback and provides insights into the key performance indicators that deserve the most attention in training. The system translates these insights into tangible advice for training. The user data found via interviews and observations was an exploration of the domain of hangboard training. The academic papers in the domain of hangboard training focused on proving a significant increase in the performance of the hangboarder while using an hangboard for only 4-8 weeks. A high increase in performance requires high training loads, which makes the athletes more prone to injuries. However, the injury topic was underexplored for hangboard training and was therefore brought to light via this thesis. The importance of mapping the internal loads of the athlete during training seemed approved as a method in other sports. Therefore, the frameworks used for designing training load management systems for other sports were therefore combined and readjusted and applied to hangboard training. The user was considered important in this first exploration of designing such a system. Therefore, a co-design approach was used to include the user from step one. In conclusion, the insights gathered in this thesis are the foundation for more exploration to innovate in hangboard training.

Second, a step-to-step plan to design a training load management system with a co-design approach is created that can be used by other researchers. The co-design process from figure 3.1 is a process that is applied to hangboard training. However, the created process is generic and can help other researchers to create training load management systems for other sports. Besides applying the process to other sports, the steps taken in this thesis can be further deepened for hangboard training. Therefore, the co-design process contributes on high-level and low-level.

Third, an interactive training load management system for hangboard training is designed, which can be used by climbers to streamline their training efforts. The functional prototype that was created in co-design phase III, is fully working and shows the potential of developing a KPI monitoring tool for hangboard training with a positive outcome. The outcome of the user test with a with-in subjects design gives insights into the potential of creating such a system in hangboard training. Besides, the prototype's capabilities fall within the capability range of IMUs and thus also show the potential of developing an IMU application in hangboard training.

Fourth, the prototype in co-design phase III shows that it is possible to create a lo-fi prototype in a short time frame. The prototype fitted the exploitative mindset and showed the potential for possible implementations.

4.2 Implications

The first implications of this thesis derive from the users used in the co-design process. This thesis was a case study for hangboard training but only used users aged between 18 and 30 years old. According to the interviews and surveys, this research would have found different results if younger users (children) or older users (30+) had been included. Therefore, re-doing the co-design process with other aged users should be considered as the next iteration of this thesis.

The second implication is the choice to frame this thesis' study within the capabilities of IMUs. On the one hand, this made the study more focused and helped to decrease the number of possible sensor options for the prototype. However, if another technology was taken as a lens, it could be that the research would have ended with another solution, solving the same user problems. For example, if expert hangboard athletes want a more detailed threshold, future research should evaluate the landscape of other available technologies to find viable alternatives.

The third implication is the choice of hangboard training as a case study. The co-design process is developed based on the findings from the user research with a focus on hangboard training. Then, the co-design process is generalised to a generic process that can be used in other sports to design systems that can help athletes manage their training load and prevent injuries. However, the co-design process might have been slightly different if another sport had been taken as a case study. Therefore, re-considering the co-design process can be done via the execution of another case study.

The fourth implication is the design of the prototype in co-design phase III. A rapid prototype platform is chosen to develop and test the functionalities of the prototype. The finger strength KPI, shoulder strength KPI and core strength KPI are important aspects to keep in mind in the design of a hi-fidelity prototype. Using IMUs that can sense these KPIs could take the current prototype to a new level.

The last implication is the design of the feedback system. The feedback system is created based on the design workshop from co-design phase II. However, the final test was done based on this feedback system. It could be that if the design workshop was done multiple times with different participants, the feedback design would have turned out differently. Which then, of course, could have affected the final user test. Therefore, it is helpful to re-do the user test with a different design for the feedback system to evaluate the used feedback design in this thesis.

4.3 Limitations

Besides the contributions and the implications, some limitations must be kept in mind while looking at the results of this thesis. More users could have been interviewed, and more prototypes could have been made to gather more insights to better design a solution for hangboard training. However, as time is an essential factor, both are minor limitations. The most significant limitation of this thesis lies within the final user test to prove a statistically significant difference in performance while training on the hangboard with the provided feedback.

The user test was done with 12 participants, but it is recommended to use more than 30 participants [29]. However, as time was limited, it was impossible to execute the test with more than 30 participants. Next, a within-subjects design was chosen even though a between-subject design might have been a better option to get less affected by the carryover effect as mentioned in section 3.3.1. However, as a between-subjects design requires even more participants, it was not possible to execute the user test with a between-subjects design. In addition, in the ideal situation, the user test was executed over several months to evaluate better the feedback's impact on the athlete's performance. However, again the lack of participants and the lack of time made this impossible. It could be that the user test would have had other results if more participants were included or if another test design was used.

4.4 Future Work

The previous section dived further into the contributions, implications and limitations. The implications and limitations of this research can be resolved via future work. Besides, there are some unexplored possibilities which are left for future research.

First, at the end of section 2 State of The Art, it is proposed to use a readiness test at the start of each training to estimate the internal load of the athlete before the external loads are set. However, this thesis did not dive further into the possible execution of this readiness test and left this opportunity for future research. Nevertheless, from the qualitative data of the user test in co-design phase III, it came forward that the prototype could also be used as a readiness test. However, the possible implementation of this is not yet investigated.

Second, the prototype of co-design phase III consists of three parts, the ultrasonic sensor, the stretch sensor and the accelerometer. These sensors are only tested together in one prototype and not independently. The user research showed that a t-shirt with a stretch sensor could benefit beginner hangboarders. For future research, it seems interesting to investigate the sensors independently and decide on other possible sensor setups.

Third, it would be interesting to investigate if the generic co-design process created based on this case study works for other sports. Therefore, it is recommended that future research will look into other sports to fine-tune the proposed process further. Fourth, from the interviews, it came forward that it would be interesting if the system created during this thesis could be integrated into other existing apps. Therefore, it seems interesting to investigate a business model for the prototype to find potential selling markets. The prototype can be improved toward their specific desires based on the interested clients.

And fifth, the prototype is now designed with the idea that the athlete could evaluate his behaviour. Even though the trainer could use this information, the prototype is not per se designed for the trainer. Therefore, investigating if the trainer could benefit from such a system is left for future work.

4.5 Conclusion

In conclusion, this thesis is the first step toward a training load management system for hangboard athletes to prevent injuries. The system helps the user by identifying and notifying his internal load capacity. The insights gained from the system help the user better tune his external training load to reach his desired training outcome without risking injuries. The steps taken for hangboard training can be further explored and elaborated for future purposes. Besides, the design approach of this thesis can be generalised into a step-to-step plan (figure 4.2), which can be applied to other sports.

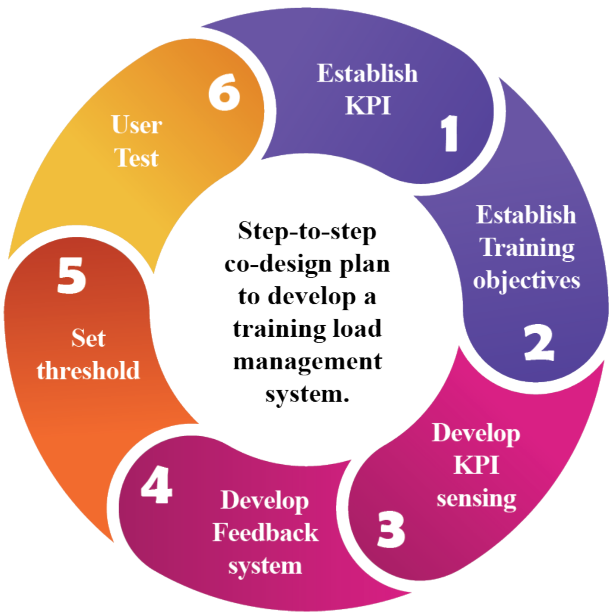


FIGURE 4.2: The step-to-step plan to develop a training load management system to prevent injuries: a co-design approach.

Bibliography

[1] Load, overload, and recovery in the athlete: Select issues for the team physician—a consensus statement. *Current Sports Medicine Reports*, 18(4):141–148, 2019.

[2] Ibrahim Akubat, Grant Abt, Richard J Lovell, and Lars McNaughton. A comparison of methods for the calculation of the training impulse. In *British Journal of Sports Medicine: Volume 43, Issue 11: International Sports Science and Sports Medicine Conference Abstracts*, 2009.

[3] Ibrahim Akubat, Steve Barrett, and Grant Abt. Integrating the internal and external training loads in soccer. *International journal of sports physiology and performance*, 9(3):457–462, 2014.

[4] Michael L Anderson, Mark L Anderson, and Adam Sanders. An innovative hangboard design to improve finger strength in rock climbers. *Procedia engineering*, 147:269–274, 2016.

[5] Dicle Aras, Selcuk Gul, Firat Akca, Mehmet Gulu, Özkan Güler, Cemil Bildircin, Erşan Arslan, and Güney Çetinkaya. Four-week of local electromyostimulaiton training on fingerboard increases the isokinetic wrist strength and endurance. *Physical education of students*, 24(3), 2020.

[6] Blaine E Arney, Reese Glover, Andrea Fusco, Cristina Cortis, Jos J de Koning, Teun van Erp, Salvador Jaime, Richard P Mikat, John P Porcari, and Carl Foster. Comparison of rpe (rating of perceived exertion) scales for session rpe. *International journal of sports physiology and performance*, 14(7):994–996, 2019.

[7] Jiří Baláš, Jan Gajdošík, David Giles, Simon Fryer, Dominika Krupková, Tomáš Brtník, and Andri Feldmann. Isolated finger flexor vs. exhaustive whole-body climbing tests? how to assess endurance in sport climbers? *European journal of applied physiology*, 121(5):1337–1348, 2021.

[8] Jiří Baláš, Michail Michailov, David Giles, Jan Kodejška, Michaela Panáčková, and Simon Fryer. Active recovery of the finger flexors enhances intermittent handgrip performance in rock climbers. *European journal of sport science*, 16(7):764–772, 2016.

[9] Jack J Baroudi, Margrethe H Olson, and Blake Ives. An empirical study of the impact of user involvement on system usage and information satisfaction. *Communications of the ACM*, 29(3):232–238, 1986.

[10] Eric Boyer, Frédéric Bevilacqua, François Phal, and Sylvain Hanneton. Low-cost motion sensing of table tennis players for real time feedback. *Int. J. Table Tennis Sci*, 8:1–4, 2013.

[11] Gian Luigi Canata, Valentina Casale, Marco Davico, and Simone Lapi. Muscle injuries. In *The Sports Medicine Physician*, pages 187–195. Springer, 2019.

[12] Farzin Dadashi, Florent Crettenand, Grégoire P Millet, Ludovic Seifert, John Komar, and Kamiar Aminian. Automatic front-crawl temporal phase detection using adaptive filtering of inertial signals. *Journal of sports sciences*, 31(11):1251–1260, 2013.

[13] Michael K Drew and Caroline F Finch. The relationship between training load and injury, illness and soreness: a systematic and literature review. *Sports medicine*, 46(6):861–883, 2016.

[14] Ned Feehally. *Beastmaking: A Fingers-First Approach to Becoming a Better Climber*. Vertebrate Publishing, Sheffield, 2021.

[15] Simon Fryer, Lee Stoner, Keeron Stone, David Giles, Joakim Sveen, Inma Garrido, and Vanesa España-Romero. Forearm muscle oxidative capacity index predicts sport rock-climbing performance. *European journal of applied physiology*, 116(8):1479–1484, 2016.

[16] Tim J Gabbett, Steve Kennelly, Joe Sheehan, Richard Hawkins, Jordan Milsom, Enda King, Rod Whiteley, and Jan Ekstrand. If overuse injury is a 'training load error', should undertraining be viewed the same way?, 2016.

[17] Monoem Haddad, Georgios Stylianides, Leo Djaoui, Alexandre Dellal, and Karim Chamari. Session-rpe method for training load monitoring: validity, ecological usefulness, and influencing factors. *Frontiers in neuroscience*, 11:612, 2017.

[18] Shona L Halson. Monitoring training load to understand fatigue in athletes. *Sports medicine*, 44(2):139–147, 2014.

[19] Espen Hermans, Atle H Saeterbakken, Vegard Vereide, Ivar SO Nord, Nicolay Stien, and Vidar Andersen. The effects of 10 weeks hangboard training on climbing specific maximal strength, explosive strength, and finger endurance. *Frontiers in Sports and Active Living*, 4, 2022.

[20] Patria A Hume, Duncan Reid, and Tony Edwards. Epicondylar injury in sport. *Sports Medicine*, 36(2):151–170, 2006.

[21] Franco M Impellizzeri, Paolo Menaspà, Aaron J Coutts, Judd Kalkhoven, and Miranda J Menaspa. Training load and its role in injury prevention, part i: back to the future. *Journal of athletic training*, 55(9):885–892, 2020.

[22] Franco M Impellizzeri, Ermanno Rampinini, Aaron J Coutts, ALDO Sassi, Samuele M Marcora, et al. Use of rpe-based training load in soccer. *Medicine and science in sports and exercise*, 36(6):1042–1047, 2004.

[23] Hibiki Kawano, Sho Yokota, Akihiro Matsumoto, Daisuke Chugo, and Hiroshi Hashimoto. Design and basic experiment of online feedback training system for golf putting. In *2021 IEEE/SICE International Symposium on System Integration (SII)*, pages 223–228. IEEE, 2021.

[24] Göran Kenttä and Peter Hassmén. Overtraining and recovery. *Sports medicine*, 26(1):1–16, 1998.

[25] Gideon Keren. Between-or within-subjects design: A methodological dilemma. *A handbook for data analysis in the behaviorial sciences*, 1:257–272, 2014.

[26] Angie M Kingsley. *The effects of hangboard exercise on climbing performance and grip strength in college age female indoor rock climers*. PhD thesis, 1997.

[27] Sari Kujala. User involvement: a review of the benefits and challenges. *Behaviour & information technology*, 22(1):1–16, 2003.

[28] Michael Ian Lambert and Jill Borresen. Measuring training load in sports. *International journal of sports physiology and performance*, 5(3):406–411, 2010.

[29] Jonathan Lazar, Jinjuan Heidi Feng, and Harry Hochheiser. *Research methods in human-computer interaction*. Morgan Kaufmann, 2017.

[30] Alejandro Lucía, Jesús Hoyos, Alfredo Santalla, Conrad Earnest, and José L Chicharro. Tour de france versus vuelta a espana: which is harder? *Medicine & Science in Sports & Exercise*, 35(5):872–878, 2003.

[31] Jerry PJ Medernach, Heinz Kleinöder, and Helmut HH Lötzerich. Fingerboard in competitive bouldering: training effects on grip strength and endurance. *The Journal of Strength & Conditioning Research*, 29(8):2286–2295, 2015.

[32] Iñigo Mujika. Quantification of training and competition loads in endurance sports: methods and applications. *International journal of sports physiology and performance*, 12(s2):S2–9, 2017.

[33] Saskia Mundry, Gino Steinmetz, Elizabeth J Atkinson, Arndt F Schilling, Volker R Schöffl, and Dominik Saul. Hangboard training in advanced climbers: A randomized controlled trial. *Scientific reports*, 11(1):1–8, 2021.

[34] DEES B.W. POSTMA. Sports, data, and interaction – taxonomy of a design space of science and technology.

[35] David A Quillen, Mark Wuchner, and Robert L Hatch. Acute shoulder injuries. *American Family Physician*, 70(10):1947–1954, 2004.

[36] Samir A Rawashdeh, Derek A Rafeldt, and Timothy L Uhl. Wearable imu for shoulder injury prevention in overhead sports. *Sensors*, 16(11):1847, 2016.

[37] Per Renström and Robert J Johnson. Overuse injuries in sports. *Sports Medicine*, 2(5):316–333, 1985.

[38] Dominik Saul, Gino Steinmetz, Wolfgang Lehmann, and Arndt F Schilling. Determinants for success in climbing: A systematic review. *Journal of Exercise Science Fitness*, 17(3):91–100, 2019.

[39] Roland Sigrist, Georg Rauter, Laura Marchal-Crespo, Robert Riener, and Peter Wolf. Sonification and haptic feedback in addition to visual feedback enhances complex motor task learning. *Experimental brain research*, 233(3):909–925, 2015.

[40] Roland Sigrist, Georg Rauter, Robert Riener, and Peter Wolf. Augmented visual, auditory, haptic, and multimodal feedback in motor learning: a review. *Psychonomic bulletin & review*, 20(1):21–53, 2013.

[41] Eric J Sobolewski. The relationships between internal and external load measures for division i college football practice. *Sports*, 8(12):165, 2020.

[42] Nicolay Stien, Helene Pedersen, Vegard A Vereide, Atle H Saeterbakken, Espen Hermans, Jarle Kalland, Brad J Schoenfeld, and Vidar Andersen. Effects of two vs. four weekly campus board training sessions on bouldering performance and climbing-specific tests in advanced and elite climbers. *Journal of Sports Science & Medicine*, 20(3):438, 2021.

[43] Wolfgang Teufl, Markus Miezal, Bertram Taetz, Michael Fröhlich, and Gabriele Bleser. Validity of inertial sensor based 3d joint kinematics of static and dynamic sport and physiotherapy specific movements. *PloS one*, 14(2):e0213064, 2019.

[44] Thiago Ferreira Timoteo, Paula Barreiros Debien, Bernardo Miloski, Francisco Zacaron Werneck, Tim Gabbett, and Maurício Gattás Bara Filho. Influence of workload and recovery on injuries in elite male volleyball players. *The Journal of Strength Conditioning Research*, 35(3):791–796, 2021.

[45] Lee K Wallace, Katie M Slattery, Franco M Impellizzeri, and Aaron J Coutts. Establishing the criterion validity and reliability of common methods for quantifying training load. *The Journal of Strength & Conditioning Research*, 28(8):2330–2337, 2014.

[46] Nerys Williams. The borg rating of perceived exertion (rpe) scale. *Occupational Medicine*, 67(5):404–405, 2017.

[47] F Wittmann, T Di Pietro, A Béguelin, S Meier, E Wilhelm, and P Wolf. A robot for climbing specific finger strength assessment and training with reduction in shoulder load. In *CONGRESS BOOK*, page 66, 2021.

[48] Ze Wu, Jiwen Zhang, Ken Chen, and Chenglong Fu. Yoga posture recognition and quantitative evaluation with wearable sensors based on two-stage classifier and prior bayesian network. *Sensors*, 19(23):5129, 2019.

[49] Jingzhen Yang, Abigail S Tibbetts, Tracey Covassin, Gang Cheng, Saloni Nayar, and Erin Heiden. Epidemiology of overuse and acute injuries among competitive collegiate athletes. *Journal of athletic training*, 47(2):198–204, 2012.

[50] Gwangjae Yu, Young Jae Jang, Jinhyeok Kim, Jin Hae Kim, Hye Young Kim, Kitae Kim, and Siddhartha Bikram Panday. Potential of imu sensors in performance analysis of professional alpine skiers. *Sensors*, 16(4):463, 2016.

[51] Shaghayegh Zihajehzadeh, Darrell Loh, Tien Jung Lee, Reynald Hoskinson, and Edward J Park. A cascaded kalman filter-based gps/mems-imu integration for sports applications. *Measurement*, 73:200–210, 2015.

Chapter 5

Appendix

5.1 Appendix A: Research Topics Paper

What the current state-of-the-art of IMUs means for the design of interactive applications in sports.

Amber Eggengoor s1928333

March 14, 2022

1 Introduction

Inertial measurement units (IMUs) have exploded in popularity over the last decade and their use is not longer ignored in the domain of sports. Using IMUs in monitoring and analysing sport movements has become common place in sports research since it avoids the laboratory limitation [1] and gives the trainers and coaches the ability to provide precise feedback [2]. Many researchers have investigated the value of having those IMUs in different sport environments (visible in table 1) focusing on measuring movements [3] [4] [5] [6] [7] [8] [9], classification of movements [10] [2] [11] [12] [13] [14], impact detection [15] [16] [17] [9], and performance analysis [18] [19] [20] [21].

Badminton	[3]
Cricket	[10]
Football	[15]
Rugby	[16]
Swimming	[4] [2]
Gymnastics	[11]
Golf	[12] [5]
Skiing	[18] [13]
Yoga	[19]
Running	[17]
The gym	[14] [20]
Dancing	[6]
Rowing	[7]
Tennis	[21] [8] [9]
Bowling	[22]

Table 1: IMU use cases in different sport environments (examples)

According to literature papers, IMUs give the possibility to find the tiniest flaws in the athlete's posture and movements, which can bring personal bests to a new level and can help avoiding injuries [23]. An IMU is a combination of multiple inertial sensors: an accelerometer (measures acceleration), a gyroscope (measures angular velocity), and can also include a magnetometer (measures magnetic field, to calculate the orientation of the sensor) or barometer (measures atmospheric pressure, to approximate the altitude of the sensor), as visible in figure 1 [24] [25].

The output of an IMU is raw data which can be refined and transformed into digestible metrics by using algorithms and task specific calculations. The combination of the hardware (IMU) and the software (including the algorithms) can provide the real value to the end-user: posture and movement recognition and training. As mentioned earlier, researchers have investigated IMUs in different sports environments. However, most of those papers are about one sport in specific and do not dive further into or compare their findings with other sports. Next to this, papers that investigate interactive applications with IMUs do not dive further into the chosen interaction. It seems that existing work especially investigates IMU applications from the sensing perspective (technology-centered), while the interaction domain (user-centered) stays an unexplored domain. Exploring the interaction domain is beneficial for (interactive) training applications as approaching it from a user-centered view can lead to new and promising applications. It is imaginable that the technology is not capable of reaching the desired accuracy, but this could be compensated by the implementation of a certain user interaction. So, it might be still possible to create an effective and fitting IMU application, even if the technology is not at a specific accuracy level. Therefore, the goal of this paper is to review existing academic work, to explore interaction possibilities. And thereby find out what the current state-of-the-art of IMUs means for the design of interactive applications in sports. This paper is the first step towards more immersive interactive IMU applications.

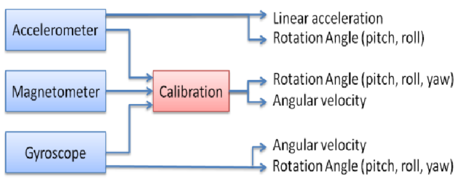


Figure 1: IMU based on three type of sensors [24]

2 From sensor data to interactive coaching and learning applications

In the sports domain, camera and video based systems are recognised as the golden standard [26]. Therefore, IMUs should at least be on par with this technology in order to stand a chance of being a good or even better alternative. Several studies have proven that the data from the IMUs, for both static and dynamic movements, have an excellent correspondence with the data from the video-based and camera-based system [27] [28]. Besides the fact that the output of IMUs come close to the output of video-based and camera-based systems, IMUs are more suitable in sport environments due to (1) the fast, reliable and cost-efficient processing process [2] [25] [26], (2) the small weight and thus the portability [29] [30], (3) the ability to provide a greater range of useful quantitative variables for sports applications [28], and (4) the system is not limited to a confined space (laboratory), making it suitable for sport activities that happen over large distances such as skiing and snowboarding [28] [31]. So, an IMU application is a promising technology to enhance sports training and support athletes. However, how can the data of the IMUs be translated in an accessible way to the user (athlete), so that he can improve his performance? This question can be answered by means of the data science life-cycle[1] and the CRISP-DM process model for data mining [32]. From this, it can be understood what phases the data go through before it is provided to the user.

Phase 1: Measure and Collect. This first phase is about measuring and collecting data on the movement/posture. There are several IMUs commercially available and each have their own specifications, data collection procedures and raw data quality [33]. It is important to identify the best-suited IMUs depending on the needs of the project. The accuracy of the data can be improved in this first phase, by putting effort into finding the optimal sensor location and orientation [34] [35]. Next to this, the set-up (number of sensors) needs to be considered, as this also contributes

[1]https://ischoolonline.berkeley.edu/data-science/what-is-data-science/

to the quality of the raw data [36].

Phase 2: Store and Clean. After the data collection, the data has to be stored and cleaned. During the cleaning process, data errors are detected and removed in order to improve the quality of the data [37]. Errors in data can be found via multiple ways, such as filtering, smoothing or outlier analysis. After the data set is cleaned, a storage medium is used to store the data for further processing. This storage can be on physical hardware, but due to today's fast internet connection, those data sets are often stored in online databases (cloud) [6].

Phase 3: Analyse and Model. Now the clean data is stored, the data can be analysed and modelled. There are current studies that review different algorithms for activity recognition and detection with IMUs [35] [38]. However, it is claimed that no proposed algorithm can be preferred over the others, as the algorithm is task and goal specific. Nevertheless, the results of the review can help other researchers by making it easier to choose between the algorithms for their specific project.

Phase 4: Use and Communicate. During the first three phases, data scientists, algorithm engineers, and mathematicians try their best to maintain the highest data quality as possible. Therefore, the more important is the last and fourth phase, as the last step does not want to waste this maintained quality. This importance is visible in the number of existing papers that investigate dashboards-communicating insights from the IMU-data with trainers/athletes. This is interesting as the communication phase is the final step which translates the data to the user. From an Interaction Technologist perspective, there are way more communication methods that go beyond these investigated dashboards. The translation should be chosen carefully in order to design meaningful and exciting interactive applications for sports. This review dives further in this communication stage, to investigate what IMUs can mean for the design of smart sports exercises.

3 Feedback strategies and User Interaction: The fourth phase of the IMU data

As mentioned in the previous section, there are different communication methods possible for interactive IMU applications in sports. Existing studies will be compared to get a good understanding of their IMU implementations and the used feedback strategies to find the guiding principle behind it. It is assumed that the usability of the IMU data during a sport exercise will decrease rapidly if the data is not appropriately communicated to the user. Therefore, it is not only the usefulness of the IMU data that determines learning success, but it is the design of the feedback that matters.

3.1 Data monitoring

Data monitoring can help the athlete to quantify their performance. This is especially useful for athletes who want to optimise their posture. This process of optimising postures can be of great value in various sports, for example in a sport as yoga. One of the main problems for Yoga beginners is to know whether they perform the yoga postures correctly, without exactly knowing their joint angle. A full-body suit consisting of 11 IMUs, as in figure 2, can make it possible for the user to understand their joint angle, correct this towards the wanted angle and thereby decrease the joint angle errors significantly [19]. By the use of IMUs, it is possible to create quantitative evaluation methods to recognise and evaluate motions and postures and to provide guidance to the learner. However, this understanding is not as intuitive and accessible as it could be. The interaction with IMUs that is often seen in current

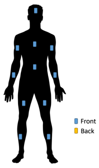


Figure 2: Full-body suit for Yoga [19]

research is data recording and data monitoring (the process of proactively reviewing and evaluating the data and its quality to ensure that the user can improve its performance, postures and motions) [39]. Besides that this data monitoring can be helpful for the user to review his performance after the work-out/training, it is not often implemented in such a way that the user can review his performance during the training. The latter, real-time feedback, is beneficial for the athlete's self-motion perception and faster learning success, consequently, real-time feedback has a positive effect on the performance development of athletes [40]. Next, real-time feedback can help to alert and inform the athlete to adjust their posture and motions on the spot. Adding signalling to systems that only monitor data, can help to make those applications more towards meaningful smart sports exercises.

3.2 Data monitoring and signalling

Many sports injuries are due to high load demands during a work-out/training and could use signalling to prevent these injuries [16] [39]. As it has been proven that IMUs can be helpful in detecting the workload on specific joints [16]. Implementing these sensors in a training makes it possible to not only monitor workload but also issue preventative warnings. This does not mean that any injury can be prevented [41]. However, the insights on workload might help to better plan rest breaks in order to decrease the possibility of getting injured. Next to this, the insights can help the trainers/coaches to understand the load volume of their training and adjust accordingly [16]. One example study focuses on the hitting load in tennis [9]. The study proves that it is possible to quantify shot counts and proves to be able to discriminate shot types. However, the study does not focus on signalling the athlete when hitting the ball too hard or when the athlete's intensity (work load vs time) is too high. Nevertheless, a trainer is able to watch the data coming from the IMUs to makes sense of the data and prevent the athlete from work overload. Another example study focuses on detecting fatigue in outdoor running [17]. This study claims to be successful in detecting and predicting fatigue (weakening of the performance) during an outdoor run but did not go further into the signalling part. This means that the paper does represent a good start for moving IMU technology into a real-world application, however this application is not yet further explored. Besides these studies, there are studies that do focus on signalling the user. One example is a study that focus on upper limb posture correction with haptic feedback [42]. The described system gives feedback on upper limb posture via vibration patterns (haptic feedback). From this research it became clear that more complex posture might need additional feedback mode to maintain fast posture correction. The last study is a good example of real-time signalling the user during his activity. Besides haptic feedback, signalling the user can be done via visual or auditory modalities, either in isolation or in combination (multi-modal) [43].

3.2.1 Visual feedback

Data visualisations of the user's performance is often presented to the user after he has finished the exercise [30]. The data from the IMUs can be uploaded to the cloud or a computer, where the data is processed. The analytic engine can then provide 2D feedback (data charts) to the player for enhancing their performance while also preventing potential injuries [8]. Besides 2D analysis, 3D analysis has been investigated by related studies [44]. 3D analysis is more accurate than 2D analysis, as 2D analysis cannot be used to determine the external or internal rotations as this movement occurs in the transverse plane [45]. Therefore, using 3D analysis to detect and prevent injuries is advised. Next to 2D analysis and 3D analysis, live analysis seem to be promising too. In fact, it is proven that real-time 3D-feedback based on IMUs is technically and conceptually feasible [46]. A good example of where real-time feedback is proven to be helpful is in a study about motion mimicking [47]. This study investigated participants who had to mimic the motions of the instructor in a video. IMUs were placed on the participants body and based on this data, visual feedback was given on the accuracy of their mimicking movements by comparing the relevant joint angle data. There was a significant difference in accuracy level found when group A (no-feedback) and group B (feedback) were compared. So, the key implication of this study is that visual feedback can provide an extrinsic source that helps the user to better synchronise their movements during their mimicking process [47]. This is an interesting finding which might be helpful in sports training as well, as then demonstrated movements can easier be repeated (self-modelling/expert-modelling [48]). Besides representing the IMU data via visuals, IMU data can also be used as a remote controller to interact with a visual display. HulaMove [49] is an good example of an IMU application that gives the user the opportunity to interact with a visual device without using their eyes and hands. HulaMove is an interaction technique that uses an IMU to measure waist movements to let the user interact with for example their phone to change volume or skip the current music song. This is also an interesting way of combining IMU data with visual feedback, as this can be applied to sports as well. Imaginably, IMUs can help to transform 'boring' drills in a sports training to an engaging and fun exercise. In addition, despite it might be helpful for the trainer to receive visual feedback of the athlete during the exercise, the athlete might not have the time and vision to look at a screen. In situations in which that is the case, the visual modality might not be the right fit, and other modalities should be explored.

3.2.2 Auditory feedback

Using the auditory modality as the feedback strategy is proven to be an effective and pleasant way to provide information fast enough to embody the player's movements [50] [51] [52]. In ball sports such as golf, volleyball and football, the athletes gaze at the ball before hitting it. Therefore, auditory feedback could be a better solution than visual feedback, as visual feedback is not realistic due to impede gazing at the ball [53]. Popular exercises in ball sports are drill exercises. In those drill exercises, it is desired that the athlete repeats the same movement until mastery is achieved. However, it is often hard for the athlete to understand the differences between his/her movements inside this drill. Even though the athlete might feel two movements as similar, it is hard the quantify this [7]. Auditory feedback based on IMU data can help the athlete during his/her self-assessment by providing direct information on the performed movements [54]. When the athlete understands his/her performed movement, repeating the movement will be easier and the movement repeatability of the athlete will increase [53]. Besides the practical advantages of the auditory feedback, high-dimensional data can be presented via auditory feedback due to the high number of sound dimensions (loudness, pitch or timbre) combined with auditory display attributes (timing or localisation) [43]. Next, the auditory modality remains largely available without interfering with other modalities and can be processed rapidly [54].

3.2.3 Haptic feedback

Another feedback strategy that does not require eyesight is haptic feedback. Haptic feedback is less invasive and less expensive compared to visual feedback and has the potential to revolutionise the way athletes engage in training [55]. Haptic feedback is found to be feasible in multiple studies: as a vibrating wrist-mounted single unit [56], vibrotactile duo unit on abdomen and back [57], and as a vibrating 4-unit ankle band [58]. In all these studies, haptic feedback is perceived by the users as intuitive and not restricting in their movements. Besides this, the haptic feedback can easily be implemented in real-world training environments, which is imaginably desired by both athletes and coaches. An example study that showed promising results was experienced positive and usable by the the participants [59]. The study developed a wearable that provided haptic feedback on postures and movements during a workday. Even though the study was focused on the working industry, the findings are promising for the sports domain as well as it proved that haptic feedback supports learning on how to improve postures and movements [59].

3.2.4 Multi-modal feedback

The previous sections discussed different feedback strategies (visual, auditory and haptic feedback) in isolation. However, these feedback strategies can also be combined to a multi-modal feedback strategy. Multi-modal feedback is overall perceived as a more natural interaction as users are used to their daily life in which they interact with their environment multi-modally (eyesight, hearing, taste, touch and smell) [60]. Next to this, multi-modal feedback is a more immersive feedback strategy than the feedback strategies in isolation [43]. Noteworthy, multimodal feedback is often a combination of visual and auditory [61], or visual and haptic [62] [63]. The addition of auditory feedback to visual feedback seem to help the user to better understand their movement velocity [64] while the addition of haptic feedback helps the athlete to find and maintain the correct rhythm and pace [63].

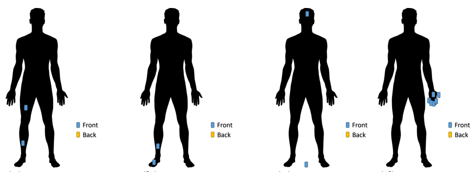
4 Posture and motion recognition with IMUs: capability, validity and reliability

Currently, the athlete's coach/trainer has an important role in posture and motion recognition during a training. Considering this task without the use of technology, the trainer observes and assesses the athlete with his own eyes and from experience and knowledge he provides (fitting) feedback. Enhancing the trainer by the use of technology can help him to provide more feedback (quantitatively) and preciser feedback (qualitatively). However, this raises the following question: Are IMUs capable of measuring those postures and motions? In IMU related research, the validity of an IMU measuring static postures and dynamic movements often arises from the IMU data in comparison with data from video-based or camera-based systems [27] [28] [2].

4.1 The influence of sensor placement on the measurement capabilities

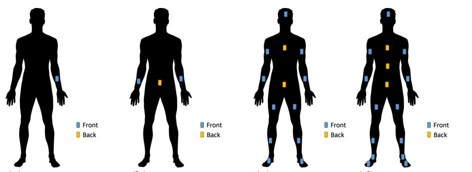
Multiple researchers have investigated using IMUs to measure and understand static postures and dynamic movements. A statement that stands out in these studies: ”For complex sequences of motion, multiple synchronised IMUs are necessary in order to achieve a high level of accuracy” [25]. Many of these studies have focused on preventing and/or correcting postures during a certain activity. For example, IMU sensors that can be used as a method to analyse head postures [65]. In this research, users are corrected in their posture while sitting on a chair. The IMU, located in the neck, can measure the angle of the neck and provide feedback to the user to prevent (further) neck injuries. However, even though the anatomy of the human is known, the placement of the IMU or a set of IMUs seems to be key in measuring (a specific part of) the human body, but there is a lack of research regarding optimal sensor placement [26]. Obviously, it can differ per posture/motion what the 'optimal' sensor placement can and may be. For example, during cycling, the knee could technically be the best place for the sensor. However, it still might not be the best place to implement due to practical issues. However, after locating the optimal placement from the user's perspective, the orientation of the IMU also have its impact on the data output. Despite that orientation errors result in larger accuracy decrease, the orientation issues can be easier corrected via calibration methods compared to location errors [34]. Besides the users comfort, it is important to know the capability of the sensors and its ability to detect certain postures/motions. The difference between running and walking might not be measurable in the pelvis, but might be at the ankles. In conclusion, both the technical capabilities of the sensor and the user's comfort should be considered while placing the sensors, especially during long-term deployment [66]. Since the goal of an interactive IMU application is to measure characteristics the athletes wishes to improve without restricting their motion in any way. [67].

As there are no guidelines for placing IMUs on the human body, different studies are compared to find similarities. Figure 3 and figure 4 show the measurements done by other researchers together with their used IMU placements. As visible in figure 3 and figure 4, measuring joint angles (knee, elbow, wrist, neck, etc.) is often done with at least two IMUs. These two IMUs are necessary, because both the positions of the connected limbs have to be measured to calculate the angle of the intermediate joint. In case of measuring rotation of a limb, only one IMU seems to be necessary on the limb that interests you. Full-body motion can be done from a few sensors but the more IMUs the more accurate data becomes available.



(a) Knee Angle [68] [69] (b) Ankle angle [70] (c) Head posture [65] (d) hand posture [71]

Figure 3: IMU placement of posture measurement



(a) Elbow rotation [3] (b) Inter-arm motion [2] (c) Full body motion [72] (d) Full body motion [18]

Figure 4: IMU placement of motion measurement

4.2 Complexity of movements

Future innovation is likely to strive for measuring complex movements with high accuracy via simple setups, to maintain and/or achieve a user friendly environment. The measurement solution should adjust according the complexity of the movement in order to reach the same accuracy. However, as it is not desired to make more complex setups when the movements become more complex, others steps should be taken. Fortunately, there are studies that investigated optimisation of the measurement accuracy of complex movements by using more sensors in their system. These studies show that it is possible to optimise the IMU measurements by adding more sensors such as electromyography sensors (EMG) [73], force plates [74] or GPS sensors [75]. It is found that adding theses sensors result in an high measurement accuracy for both complex and simple movements [76]. However, adding more sensors close to each other can also result in noise and errors in the measurements [77]. So, a reverse trend is also happening, in which researchers strive for minimal-sensor setup, and thus remove sensors from the system [78] [79] [80]. The results of these studies reveal that reducing the sensor setup does not have to result in a lower accuracy level or a lower classification performance. Therefore, the researcher should consider (per use case) if adding more sensors to the setup would give that extra in-depth information about the movement that is desired. The complexity of the movement does not only influence the technical capability of the IMUs, but also influences the interaction. Complex movements are more difficult to learn than simple movements and athletes are likely to need more guidance while learning these complex movements. Next to this, complex movements ask for more precise feedback for the athlete to improve the movement. Therefore, the reliability and validity of the IMUs become more important in more complex movements.

4.3 Validity and Reliability of IMUs

Alone, each sensor provides biased information under certain circumstances, but putting them together (sensor data fusion) allows their limitations to be overcome and provides more accurate sensor orientation [26] [30]. However, in order to get an high accuracy from the data fusion, it is important to consider the reliability of each sensor. Different studies have investigated the reliability of the IMUs and came to the conclusion that IMUs appear to provide a suitable alternative to Video-based or camera-based motion capture systems. It is found that the IMUs especially reach an high accuracy while capturing flexion/extension movements at the lower limb joints during simple movements [26]. However, it is claimed that the degree of accuracy is task specific, and that the increasing movement complexity decreases the validity of the IMUs [81]. Even though the validity of the IMUs decreases, it does not mean that the data is unusable. However, it does mean that the interaction should be adjusted in such a way that the user is not subjected to false data. For example, if the location of the athlete cannot be determined precisely, it is better to represent the athlete's location as a cloud with margin rather than a dot without margin. Adjusting the interaction as in the cloud-example, the expectations of the athlete (having a precise location) is lowered and the validity issues of the data is covered. This means that the way of how the interaction is presented can cover for the data deviations. There are a lot of studies that investigate reliability and validity of IMUs. However, these studies were performed in a controlled environment (laboratory settings). Therefore, they cannot be considered as directly representing IMU performance during real-life/outside of laboratory use [26]. Next to this, the current studies did not investigate the interaction possibilities with their available data. Therefore, current studies seem to be striving for 'perfect' data quality while the goal of having this data is not discussed and might not be necessarily needed. In conclusion, the effects on the user's data perception by changing the interaction have not been investigated and is interesting for future work.

5 The potential of IMUs in sports

It has been demonstrated that IMUs have competence in applications for sports as IMUs are capable of providing valuable data on the athletes posture and movements. Despite that there are many applications found, the reasoning behind their used IMU-setup and feedback strategy seem not be discussed clearly. Previous validation studies of IMUs have been incomplete regarding aspects of complexity of movements, joints analysed, duration of trials, number and type of subjects [31]. However, as mentioned in the introduction, the application of IMUs in different sport settings have been investigated, and thoroughly explained. From literature it seems that many systems are optimised for sensing but not for application, and are in that sense irrespective to the purpose of the system. Existing studies present their set-up and feedback choices as inevitable, while these decisions can have an huge impact on the result (user perception and technical capabilities). The athlete's movement and posture in comparison with correct patterns and movement characteristics can be useful not only in problem detection and identification, but also to control the performance of desired movements. The latter is an interesting topic for the sports domain, as athletes strive for a better performance. There are different topics in which IMUs can be useful in the sports domain, for example in game tactics, engagement, assessment, physical education, and refereeing. From literature four categories stood out and are discussed below. As IMUs are capable of characterising the movements of the athletes, they are often investigated in research for skill assessment (how good was the movement), for improving technique (what part of the movement can be improved), for injury prevention (how the athlete should not move) and for movement classification (what kind of movement was this).

5.1 Skill assessment

From section 4.1 it became clear the IMUs are capable of recording and processing human posture and motion, to additionally analysing the quality of these activities. Qualifying these activities typically refer to skill assessment [82]. As mentioned earlier, IMU systems have to compete with camera and video based systems. In case of skill assessment, the biggest advantage of having IMUs instead of camera systems is the portability of the IMUs. Especially in sports as skiing, it is really hard to capture the athlete during his training, as he travels a great distance. As mentioned earlier, most of the related studies focus on one sport in specific. Besides these specialised systems, there are a few studies related to generalised skill assessment that is transferable to other application domains (healthcare, industry, etc.) [82]. It is likely that the skill level of athletes is and should be measured differently per sport, to have an accurate and meaningful skill assessment. For example in tennis, power, rhythm and gesture are important variables for skill assessment of the serve [21]. In skiing, ski motion, waist rotation, and how load is applied to the skis as well as their symmetry are important variables for skill assessment [13]. However, generalising these variables, skill assessment is often referred to notion of repeatability and motion consistency [82]. Both of these can be measured with the use of IMUs. In conclusion, skill assessment is the first potential of IMUs in sports.

5.2 Improving technique

After a skill-assessment, it is possible to improve the current skills of the athlete by looking closely at his/her technique. As IMUs are capable of quantifying movements, it is possible for the coach/trainer to optimise the athlete's technique by providing feedback on movements which a coach/trainer cannot observe accurately just with their eyes [7]. Such feedback can for example be about the angle or depth of a rowing blade in the water [7]. Besides IMUs being a tool for coaches and trainers, IMUs offer the opportunity to provide low-cost exercise technique assessment in for example body weight Squats in the gym [20]. After the task is framed (for example improving serving technique), a fitting interaction modality can be chosen in order to contribute to the learning process. Comparing IMUs with video-based systems, the IMUs can be worn by the athletes during the practice without having camera setups around the field. Next to this, IMUs are due to the small size and low-weight more insensible than video-based systems. Therefore, with IMUs the technique of the athlete can be measured and improved in a real-time situation in which the athlete forgets getting filmed or measured.

5.3 Injury prevention

Using IMUs as a bio-mechanical analysis method is not yet fully accepted in the clinical practice. This is due to a disconnect between translating the data form the sensors into a meaning full and actionable feedback for the users (reliability) [83]. Therefore, it is not yet often used as injury prevention method. However, IMUs can quantify the movements of the athletes and thereby give more insights to the coach/trainer who then can decide (if) to adjust the training accordingly. In that case, the IMUs are not (yet) a stand alone system that can replace the trainer/coach, but is more considered as a tool for the trainer/coach to make grounded decisions and give better advice to the athletes. Even though IMUs are then only considered as a tool, athletes benefit greatly by ensuring that skills are practised and performed correctly to reduce the chances of sustaining an injury [11]. Besides this, IMUs offer the opportunity to monitor the athlete performances and work-outs. This information can help the athletes to gain insights into their workload (peaks).

5.4 Classification of movements

Automating sport movement recognition and the application of IMUs has the potential to enhance both efficiency and accuracy of sport performance analysis [84]. However, as mentioned in the introduction, algorithms and task specific calculations are needed to actually make sense of the IMU data. For example, the differentiating process of tennis strokes as a forehand or backhand can be done via a machine learning process. In such machine learning process, the computer classifies and interpret the movement of the athlete by comparing it with movements in its database [85]. After processing and comparing these movements, it is possible to help the user understand his/her previous movements. Next to this, when the application understands what movement the athlete has performed, it is possible to provide feedback accordingly. For example, if the system detects that the athlete is performing a serve, it is possible to provide feedback according for example a 'perfect' serve from the database, or for example according the athlete's own serve performance. However, this understanding should be provided via an effective feedback modality.

6 Discussion

Earlier studies on IMUs in sports have found promising results for several use cases. However, beyond the use of IMUs for data review and dashboards, IMUs could be used to fuel smart sports exercises. This review explored the potential of IMUs for serving this upcoming field. This shows that more studies should be done in order to draw any conclusions on implementation methods. Especially in terms of interaction and feedback strategies, there is currently little available research. This might be because the use of IMUs in sports is an emerging technology. Next to this, the implementation of IMUs in sports are often considered from the technology perspective, while the Human Media Interaction (HMI) field seems to be forgotten. It even seems to be the case that IMUs in sports are more researched in terms of possibilities due to technology evolvement, rather than solving an user problem with an IMU driven product. The latter, involves having clear product requirements which are quite important in providing a clear visibility of usability aspects for both product developers and testers [86]. For example, creating an interactive IMU application for volleyball, it is necessary to know if the athletes would like to know more about their results, about their performance or about both. Recent Augmented Feedback research [43] [87] covers the best use of feedback modalities in order to induce enduring changes in motor learning and achieve superior performance [87]. However, each modality has its pros and cons and should be chosen wisely. Researching the best feedback modality for IMUs in a specific sport domain would be interesting and useful as future work. If more knowledge on the implementation of IMUs in sports will be gained, it is possible to see and create guiding principles. However, it should be taken into account that every sport is different and has its own nature and its training. Therefore, it is advised to keep researching sports separately to prevent overlooking significant aspects of the sport.

Based on the existing research it became clear what the current IMU development means for sports. Even though some sports are more explored than others, different capabilities of IMUs in sports came forward. IMUs are capable of measuring JL (joint and limb) angles, JL velocities, JL accelerations, and JL rotations. Besides the capability of a single sensor, data fusion of data from multiple IMUs can lead to posture and motion recognition. Available research is promising on the capabilities of IMUs in comparison with video based motion capture. However, the actual placement (location and orientation) of the IMU on the body is not often discussed in use case papers. Papers which do criticise the location and orientation of the IMU are technical papers that do not dive deeper into use cases. Therefore, it is not possible to draw conclusion on the need of having the IMU on the exact spot. This is off course comparing theoretical findings (technical papers) with practical findings (use case papers). For example, even though the measurements deviates a bit, it does not necessarily mean that it causes problems for the application. The reliability of the sensors should therefore be considered per use case, as use cases that focus on injury prevention might require more reliability than use cases that focuses on recording a volleyball serve. Thus, next to capability, reliability is an important aspect to consider before creating an IMU based sports application. However, papers that investigate reliability of IMUs are often performed in a controlled environment such as a laboratory. These controlled environments are a good way to test hypotheses. However, the most fruitful overall research approach is usually to use both laboratory and field research [88]. This is because observations in the field produce new hypotheses which can then be tested again in controlled experiments. Which brings the second opportunity for future research, investigating reliability of IMUs in a ' real-life' application.

The main challenge of this research was to find the potential of IMU applications in sports. forward that IMUs are helpful in skill assessment, in helping to improving technique, injury prevention and classification of movements. However, as mentioned in this paper, each sport is different and might require different aspects/skills from the athlete. Therefore, a specific (user)problem should be tackled so that a solution can be formed. It is found that the solution of IMUs in sports highly depend on the implementation method. Hence, choosing a fitting feedback modality is important so that the user is supported and not hampered. User tests with multiple feedback modalities (in isolation or combined) is recommend, as each feedback modality has its impact on the users perception. Current available research has not been combined into implementation guidelines, which points out the third opportunity for future research.

7 Conclusion

In current literature it is unknown what IMUs mean for the design of interactive applications in sports. IMUs are proven to be capable in measuring postures and motions of athletes and this opportunity should be used to create meaningful and effective interactive IMU sport applications. From this paper it is learnt that each sport has its own aspects and training. Therefore, it is recommended for future research to focus on one sport in specific. The goal of the case study is to examine how IMUs can be leveraged to maximise the potential of IMU driven interactive applications. This can be done via multiple steps. First, user research should be done to understand the pains and gains of the user. Second, with co-design sessions it is possible to ideate solutions for these pains and gains. From there, the third step, lo-fi prototypes can be made, which can (according to user feedback) be further developed into hi-fi prototypes. Insights from the case study can be diverged for other sports, so that more potential for IMU driven interactive applications can be found. Then, a shift in IMU applications in sports is created: from technology-driven innovation towards more user-centered problem solving.

References

[1] Veronica Bessone et al. “Validation of a new inertial measurement unit system based on different dynamic movements for future in-field applications”. In: *Sports biomechanics* (2019), pp. 1–16.

[2] Farzin Dadashi et al. “Automatic front-crawl temporal phase detection using adaptive filtering of inertial signals”. In: *Journal of sports sciences* 31.11 (2013), pp. 1251–1260.

[3] Alvin Jacob, Wan Nurshazwani Wan Zakaria, and Mohd Razali Bin Md Tomari. “Implementation of IMU sensor for elbow movement measurement of badminton players”. In: *2016 2nd IEEE International Symposium on Robotics and Manufacturing Automation (ROMA)*. IEEE. 2016, pp. 1–6.

[4] Robert Mooney et al. “Inertial sensor technology for elite swimming performance analysis: A systematic review”. In: *Sensors* 16.1 (2016), p. 18.

[5] Myeongsub Kim and Sukyung Park. “Golf swing segmentation from a single IMU using machine learning”. In: *Sensors* 20.16 (2020), p. 4466.

[6] Lanka Udawatta et al. “Motion capturing of biomechanical systems in traditional dance using IMU sensors”. In: *2017 International Conference on Electrical and Computing Technologies and Applications (ICECTA)*. IEEE. 2017, pp. 1–5.

[7] Bernd Tessendorf et al. “An imu-based sensor network to continuously monitor rowing technique on the water”. In: *2011 seventh international conference on intelligent sensors, sensor networks and information processing*. IEEE. 2011, pp. 253–258.

[8] Marko Kos and Iztok Kramberger. “Tennis stroke consistency analysis using miniature wearable IMU”. In: *2018 25th International Conference on Systems, Signals and Image Processing (IWSSIP)*. IEEE. 2018, pp. 1–4.

[9] David Whiteside et al. “Monitoring hitting load in tennis using inertial sensors and machine learning”. In: *International journal of sports physiology and performance* 12.9 (2017), pp. 1212–1217.

[10] Andrew Wixted et al. “Detection of throwing in cricket using wearable sensors”. In: *Sports Technology* 4.3-4 (2011), pp. 134–140.

[11] Elizabeth J Bradshaw and Patria A Hume. “Biomechanical approaches to identify and quantify injury mechanisms and risk factors in women’s artistic gymnastics”. In: *Sports Biomechanics* 11.3 (2012), pp. 324–341.

[12] Daniel TH Lai et al. “On the difference in swing arm kinematics between low handicap golfers and non-golfers using wireless inertial sensors”. In: *Procedia Engineering* 13 (2011), pp. 219–225.

[13] Seiji Matsumura et al. “Comfortable and convenient turning skill assessment for Alpine Skiers using IMU and plantar pressure distribution sensors”. In: *Sensors* 21.3 (2021), p. 834.

[14] Jaehyun Lee et al. “Automatic classification of squat posture using inertial sensors: Deep learning approach”. In: *Sensors* 20.2 (2020), p. 361.

[15] Paul B Gastin et al. “Tackle and impact detection in elite Australian football using wearable microsensor technology”. In: *Journal of sports sciences* 32.10 (2014), pp. 947–953.

[16] Tim J Gabbett, David G Jenkins, and Bruce Abernethy. “Physical demands of professional rugby league training and competition using microtechnology”. In: *Journal of science and medicine in sport* 15.1 (2012), pp. 80–86.

[17] Tim Op De Beéck et al. “Fatigue prediction in outdoor runners via machine learning and sensor fusion”. In: *Proceedings of the 24th acm sigkdd international conference on knowledge discovery & data mining*. 2018, pp. 606–615.

[18] Gwangjae Yu et al. “Potential of IMU sensors in performance analysis of professional alpine skiers”. In: *Sensors* 16.4 (2016), p. 463.

[19] Ze Wu et al. “Yoga posture recognition and quantitative evaluation with wearable sensors based on two-stage classifier and prior Bayesian network”. In: *Sensors* 19.23 (2019), p. 5129.

[20] Martin A O’Reilly et al. “Technology in strength and conditioning: assessing bodyweight squat technique with wearable sensors”. In: *The Journal of Strength & Conditioning Research* 31.8 (2017), pp. 2303–2312.

[21] Disheng Yang et al. “TennisMaster: an IMU-based online serve performance evaluation system”. In: *Proceedings of the 8th Augmented Human International Conference*. 2017, pp. 1–8.

[22] Tung Mun Hon, SMN Arosha Senanayake, and Nick Flyger. “Biomechanical analysis of 10-pin bowling using wireless inertial sensor”. In: *2009 IEEE/ASME International Conference on Advanced Intelligent Mechatronics*. IEEE. 2009, pp. 1130–1135.

[23] Daniel Roetenberg. *Inertial and magnetic sensing of human motion*. These de doctorat, 2006.

[24] Norhafizan Ahmad et al. “Reviews on various inertial measurement unit (IMU) sensor applications”. In: *International Journal of Signal Processing Systems* 1.2 (2013), pp. 256–262.

[25] Manju Rana and Vikas Mittal. “Wearable sensors for real-time kinematics analysis in sports: a review”. In: *IEEE Sensors Journal* 21.2 (2020), pp. 1187–1207.

[26] Isabelle Poitras et al. “Validity and reliability of wearable sensors for joint angle estimation: A systematic review”. In: *Sensors* 19.7 (2019), p. 1555.

[27] Wolfgang Teufl et al. “Validity of inertial sensor based 3D joint kinematics of static and dynamic sport and physiotherapy specific movements”. In: *PloS one* 14.2 (2019), e0213064.

[28] Shaghayegh Zihajehzadeh et al. “A cascaded Kalman filter-based GPS/MEMS-IMU integration for sports applications”. In: *Measurement* 73 (2015), pp. 200–210.

[29] Ionut-Cristian Severin. “Head Posture monitor based on 3 IMU sensors: Consideration toward Healthcare application”. In: *2020 International Conference on e-Health and Bioengineering (EHB)*. IEEE. 2020, pp. 1–4.

[30] Hugo G Espinosa et al. “Anytime, anywhere! Inertial sensors monitor sports performance”. In: *IEEE Potentials* 38.3 (2019), pp. 11–16.

[31] Xavier Robert-Lachaine et al. “Validation of inertial measurement units with an optoelectronic system for whole-body motion analysis”. In: *Medical & biological engineering & computing* 55.4 (2017), pp. 609–619.

[32] R. Wirth and Jochen Hipp. “CRISP-DM: Towards a standard process model for data mining”. In: *Proceedings of the 4th International Conference on the Practical Applications of Knowledge Discovery and Data Mining* (Jan. 2000).

[33] Lin Zhou et al. “How we found our imu: Guidelines to IMU selection and a comparison of seven IMUs for pervasive healthcare applications”. In: *Sensors* 20.15 (2020), p. 4090.

[34] Tian Tan et al. “Influence of IMU position and orientation placement errors on ground reaction force estimation”. In: *Journal of biomechanics* 97 (2019), p. 109416.

[35] Giulia Pacini Panebianco et al. “Analysis of the performance of 17 algorithms from a systematic review: Influence of sensor position, analysed variable and computational approach in gait timing estimation from IMU measurements”. In: *Gait & posture* 66 (2018), pp. 76–82.

[36] Stéphane Guerrier. “Improving accuracy with multiple sensors: Study of redundant MEMS-IMU/GPS configurations”. In: *Proceedings of the 22nd international technical meeting of the Satellite Division of the Institute of Navigation (ION GNSS 2009)*. 2009, pp. 3114–3121.

[37] Erhard Rahm and Hong Hai Do. “Data cleaning: Problems and current approaches”. In: *IEEE Data Eng. Bull.* 23.4 (2000), pp. 3–13.

[38] Chengli Hou. “A study on IMU-based human activity recognition using deep learning and traditional machine learning”. In: *2020 5th International Conference on Computer and Communication Systems (ICCCS)*. IEEE. 2020, pp. 225–234.

[39] Samir A Rawashdeh, Derek A Rafeldt, and Timothy L Uhl. “Wearable IMU for shoulder injury prevention in overhead sports”. In: *Sensors* 16.11 (2016), p. 1847.

[40] Mai Geisen and Stefanie Klatt. "Real-time feedback using extended reality: A current overview and further integration into sports". In: *International Journal of Sports Science & Coaching* (2021), p. 17479541211051006.

[41] Riccardo Izzo, Marco Giovannelli, and G Raiola. "Training load in elite goalkeepers with K-Track for monitoring performance". In: *Journal of physical education and sport* 19 (2019), pp. 1890–1896.

[42] ZQ Ding et al. "Inertia sensor-based guidance system for upperlimb posture correction". In: *Medical engineering & physics* 35.2 (2013), pp. 269–276.

[43] Roland Sigrist et al. "Augmented visual, auditory, haptic, and multimodal feedback in motor learning: a review". In: *Psychonomic bulletin & review* 20.1 (2013), pp. 21–53.

[44] Wolfgang Teufl et al. "Towards an inertial sensor-based wearable feedback system for patients after total hip arthroplasty: Validity and applicability for gait classification with gait kinematics-based features". In: *Sensors* 19.22 (2019), p. 5006.

[45] Pedro A Couto et al. "A comparison of two-dimensional and three-dimensional techniques for the determination of hindlimb kinematics during treadmill locomotion in rats following spinal cord injury". In: *Journal of neuroscience methods* 173.2 (2008), pp. 193–200.

[46] Matthias Seuter et al. "Live-feedback from the imus: Animated 3d visualization for everyday-exercising". In: *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*. 2016, pp. 904–907.

[47] Vanessa Wei-Lin Mak et al. "Effects of visual feedback on motion mimicry ability during video-based rehabilitation". In: *Cogent Medicine* 3.1 (2016), p. 1215284.

[48] DEES B.W. POSTMA. *Sports, Data, and Interaction – Taxonomy of a Design Space of Science and Technology*. URL: `https://canvas.utwente.nl/courses/8103/files/2359192?module_item_id=236669`. (accessed: 01.03.2022).

[49] Xuhai Xu et al. "HulaMove: Using Commodity IMU for Waist Interaction". In: *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 2021, pp. 1–16.

[50] Costas I Karageorghis and Peter C Terry. "The psychophysical effects of music in sport and exercise: A review". In: *Journal of Sport Behavior* 20.1 (1997), p. 54.

[51] Alfred O Effenberg. "Movement Sonification: Motion perception, behavioral effects and functional data". In: *Proceedings of the 2nd International Workshop on Interactive Sonification (ISon 2007). York, UK. Online*. 2007.

[52] Eric Olivier Boyer et al. "From ear to hand: the role of the auditory-motor loop in pointing to an auditory source". In: *Frontiers in computational neuroscience* 7 (2013), p. 26.

[53] Hibiki Kawano et al. "Design and Basic Experiment of Online Feedback Training System for Golf Putting". In: *2021 IEEE/SICE International Symposium on System Integration (SII)*. IEEE. 2021, pp. 223–228.

[54] Eric Boyer et al. "Low-cost motion sensing of table tennis players for real time feedback". In: *Int. J. Table Tennis Sci* 8 (2013), pp. 1–4.

[55] Kelly R Sheerin et al. "The effectiveness of real-time haptic feedback gait retraining for reducing resultant tibial acceleration with runners". In: *Physical Therapy in Sport* 43 (2020), pp. 173–180.

[56] Jasper Wong, Kelly Sheerin, and Hannah Wyatt. "Real-Time Haptic Feedback Systems Validity and Its Feasibility for Runners in a Real-World Training Environment". In: (2021).

[57] Giulia Ballardini et al. "Vibrotactile feedback for improving standing balance". In: *Frontiers in bioengineering and biotechnology* 8 (2020), p. 94.

[58] Simon Stock et al. "Feedi-a smart wearable foot-band for navigation and guidance using haptic feedback". In: *International Conference on Human Interaction and Emerging Technologies*. Springer. 2020, pp. 349–355.

[59] Carl Mikael Lind et al. "A wearable sensor system for physical ergonomics interventions using haptic feedback". In: *Sensors* 20.21 (2020), p. 6010.

[60] Matthew Turk. "Multimodal interaction: A review". In: *Pattern recognition letters* 36 (2014), pp. 189–195.

[61] Takashi Kuwahara, Itsuki Takahashi, and Shintaro Harikae. "A Novel Snowboard Training System Using Visual and Auditory Feedback". In: *International Conference on Human-Computer Interaction*. Springer. 2020, pp. 181–187.

[62] Ashutosh Raina, TG Lakshmi, and Sahana Murthy. "CoMBaT: Wearable technology based training system for novice badminton players". In: *2017 IEEE 17th International Conference on Advanced Learning Technologies (ICALT)*. IEEE. 2017, pp. 153–157.

[63] Laura Marchal-Crespo et al. "The effect of haptic guidance and visual feedback on learning a complex tennis task". In: *Experimental brain research* 231.3 (2013), pp. 277–291.

[64] Roland Sigrist et al. "Sonification and haptic feedback in addition to visual feedback enhances complex motor task learning". In: *Experimental brain research* 233.3 (2015), pp. 909–925.

[65] Mustafa Al-Yassary et al. "Evaluation of head posture using an inertial measurement unit". In: *Scientific reports* 11.1 (2021), pp. 1–9.

[66] Louis Atallah et al. "Sensor positioning for activity recognition using wearable accelerometers". In: *IEEE transactions on biomedical circuits and systems* 5.4 (2011), pp. 320–329.

[67] Arnold Baca and Philipp Kornfeind. "Rapid feedback systems for elite sports training". In: *IEEE Pervasive Computing* 5.4 (2006), pp. 70–76.

[68] Thomas Seel, Jörg Raisch, and Thomas Schauer. "IMU-based joint angle measurement for gait analysis". In: *Sensors* 14.4 (2014), pp. 6891–6909.

[69] Saba Bakhshi, Mohammad H Mahoor, and Bradley S Davidson. "Development of a body joint angle measurement system using IMU sensors". In: *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE. 2011, pp. 6923–6926.

[70] Ge Gao et al. "Comparison of dynamic vision sensor-based and imu-based systems for ankle joint angle gait analysis". In: *2016 2nd International Conference on Frontiers of Signal Processing (ICFSP)*. IEEE. 2016, pp. 93–98.

[71] Richard Polfreman. “Hand posture recognition: IR, sEMG and IMU”. In: (2018).

[72] Yang Zheng, Ka-Chun Chan, and Charlie CL Wang. “Pedalvatar: An IMU-based real-time body motion capture system using foot rooted kinematic model”. In: *2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE. 2014, pp. 4130–4135.

[73] João Lopes et al. “Hand/arm gesture segmentation by motion using IMU and EMG sensing”. In: *Procedia Manufacturing* 11 (2017), pp. 107–113.

[74] Roland van den Tillaar et al. “Step-to-Step Kinematic Validation between an Inertial Measurement Unit (IMU) 3D System, a Combined Laser+ IMU System and Force Plates during a 50 M Sprint in a Cohort of Sprinters”. In: *Sensors* 21.19 (2021), p. 6560.

[75] Adrian Waegli and Jan Skaloud. “Optimization of two GPS/MEMS-IMU integration strategies with application to sports”. In: *GPS solutions* 13.4 (2009), pp. 315–326.

[76] Sam McDevitt et al. “Wearables for Biomechanical Performance Optimization and Risk Assessment in Industrial and Sports Applications”. In: *Bioengineering* 9.1 (2022), p. 33.

[77] Subhojyoti Bose, Amit K Gupta, and Peter Handel. “On the noise and power performance of a shoe-mounted multi-IMU inertial positioning system”. In: *2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. IEEE. 2017, pp. 1–8.

[78] Vincent Xeno Rahn et al. “Optimal Sensor Placement for Human Activity Recognition with a Minimal Smartphone-IMU Setup.” In: *SENSORNETS*. 2021, pp. 37–48.

[79] Mohamed Irfan Mohamed Refai et al. “Portable Gait Lab: Estimating Over-Ground 3D Ground Reaction Forces Using Only a Pelvis IMU”. In: *Sensors* 20.21 (2020), p. 6363.

[80] Isabel Patzer and Tamim Asfour. “Minimal sensor setup in lower limb exoskeletons for motion classification based on multi-modal sensor data”. In: *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE. 2019, pp. 8164–8170.

[81] Antonio I Cuesta-Vargas, Alejandro Galán-Mercant, and Jonathan M Williams. “The use of inertial sensors system for human motion analysis”. In: *Physical Therapy Reviews* 15.6 (2010), pp. 462–473.

[82] Aftab Khan et al. “Generalized and efficient skill assessment from IMU data with applications in gymnastics and medical training”. In: *ACM Transactions on Computing for Healthcare* 2.1 (2020), pp. 1–21.

[83] Darragh Whelan et al. “Leveraging IMU data for accurate exercise performance classification and musculoskeletal injury risk screening”. In: *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE. 2016, pp. 659–662.

[84] Emily E Cust et al. “Machine and deep learning for sport-specific movement recognition: A systematic review of model development and performance”. In: *Journal of sports sciences* 37.5 (2019), pp. 568–600.

[85] Andreas Bulling, Ulf Blanke, and Bernt Schiele. “A tutorial on human activity recognition using body-worn inertial sensors”. In: *ACM Computing Surveys (CSUR)* 46.3 (2014), pp. 1–33.

[86] Sisira Adikari and Craig McDonald. "User and usability modeling for HCI/HMI: a research design". In: *2006 International Conference on Information and Automation*. IEEE. 2006, pp. 151–154.

[87] Moinuddin Arsalan, Goel Ashish, and Sethi Yashendra. "The Role of Augmented Feedback on Motor Learning: A Systematic Review". In: *Cureus* 13.11 (2021).

[88] Hassan A Aziz. "Comparison between field research and controlled laboratory research". In: *Archives of Clinical and Biomedical Research* 1.2 (2017), pp. 101–104.

5.2 Appendix B: Example data of five xSens DOTs on one participant during hangboard training

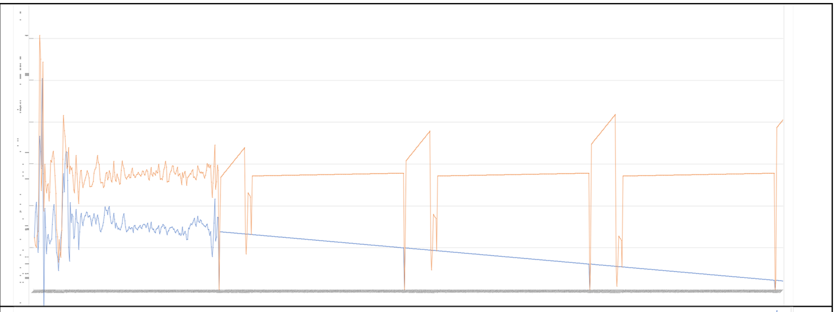
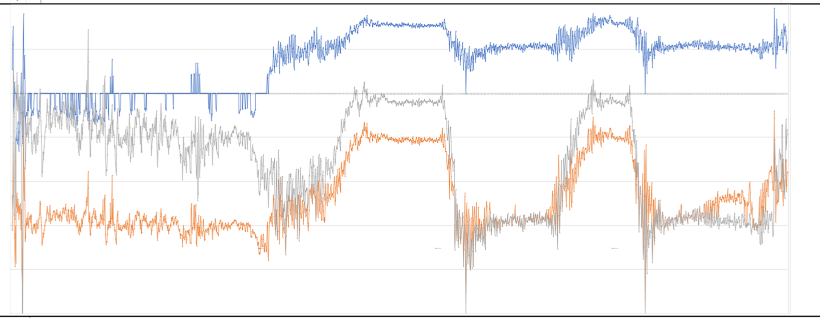
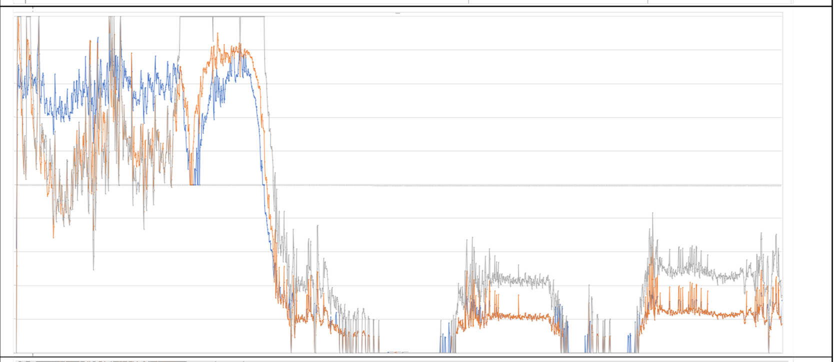
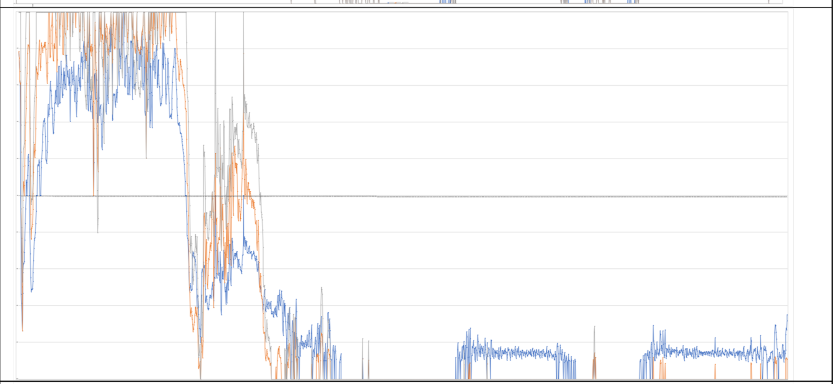
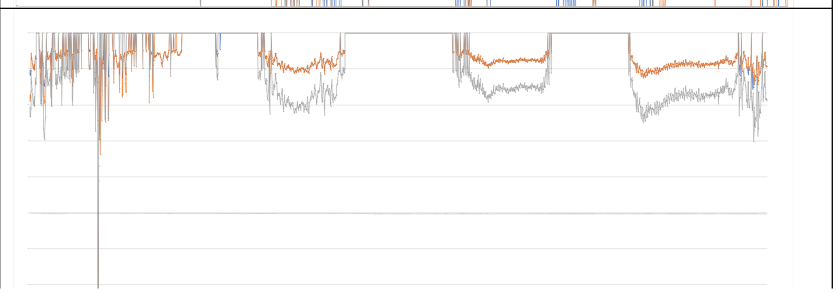
22P	Shoulder right	
22L	Shoulder left	
23P	Upper arm	
22R	Lower arm	
16P	Pelvis	

FIGURE 5.1: Example data of five xSens DOTs on one participant during hangboard training