# Video-based Training With Healthy Participants in Times of Covid-19: Monitoring of Gait and Balance Performance Independent of Location and its Impact on the General Well-being

by

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# 1 Abstract

## 1.1 English

*Introduction.* In the years 2020 and 2021, the Covid-19 pandemic and the associated restrictions have increased the demand for data collection that does not require the physical presence of participants at the study center. Instead, a measurement from home is preferred (e.g., through wearables, portable computer systems). However, no standard methods for measurements at home are currently available in gait and balance analysis. Since smartphones include accelerometers and gyroscope sensors by default and are widely available, we used smartphones as location-independent measurement devices for data collection (JTrack Social) and compared them with two standard methods of gait analysis (zebris force plates and Xsens sensor system). *Participants and Methods.* 25 healthy subjects (13 female, 44.1±18.4y, in a range of 20 to 71 years), participated in two measurements in the gait laboratory, and completed gait and balance training at home during the three-week interim period. Gait parameters and questions about general well-being and self-efficacy were collected and compared between the two measurement time points. *Results.* No effect of training on general well-being and self-efficacy was found. However, there were improvements in parameters of normal gait, backward gait and tandem gait, as well as in the narrow stance, tandem stance and single leg stance for individual systems. No improvement was found for narrow stance with eyes closed. Parameters of the force plate and the sensor system were moderately to strongly correlated, while correlation with the smartphone app data were only weak to moderate. *Discussion.* Improvements in gait and balance variables suggest positive effects of training. However, to confirm this effect, a more intense training program would be desirable for the future, as well as adjustments in the smartphone data evaluation to strive for a better agreement between the smartphone data and the data of the two standard gait analysis systems.

## 1.2 German

*Einleitung.* In den Jahren 2020 und 2021 ist durch die Covid-19 Pandemie und die damit einhergehenden Beschränkungen das Bedürfnis nach Erhebungsmethoden für Studien und klinische Untersuchungen, die keine Präsenz der Proband:innen am durchführenden Studienzentrum erfordern und stattdessen ortsungebunden z.B. auch von zu Hause aus erfolgen können (z.B. durch Wearables, tragbare Computersysteme), gestiegen. Diesbezüglich sind jedoch aktuell keine Standardmethoden in der Gang- und Balanceanalyse vorhanden. Da Smartphones standardmäßig Beschleunigungs- und Gyroskopsensoren enthalten und in der Bevölkerung weit verbreitet sind, sollten im Rahmen der vorliegenden Studie Messungen mit dem Smartphone als ortsungebundene Erhebungsmethode für zu Hause mit zwei Standardmethoden der Ganganalyse verglichen werden (Kraftmessplatten und Sensor-Systeme). *Teilnehmer und Methodik.* 25 gesunde Probanden (13 Frauen, 44,1±18,4 J., Altersspannweite von 20 bis 71 Jahren) nahmen an zwei Messungen im Ganglabor teil, und absolvierten in den drei Wochen zwischen beiden Messungen ein Gang- und Balancetraining zu Hause. Gangparameter und Fragen zum allgemeinen Wohlbefinden und der Selbstwirksamkeit wurden erhoben und zwischen den beiden Messzeitpunkten verglichen. *Ergebnisse.* Es konnte kein Einfluss des Trainings auf das allgemeine Wohlbefinden und die Selbstwirksamkeit festgestellt werden. Jedoch gab es systemspezifische Verbesserungen im normalen Gang, Rückwärtsgang und Tandemgang und im engen Stand, Tandemstand und Einbeinstand. Beim engen Stand mit geschlossenen Augen konnte keine Verbesserung festgestellt werden. Während die Daten der Kraftmessplatten und des Sensor-Systems moderat bis stark korrelierten, zeigten die Daten der Smartphone App schwache bis moderate Korrelationen. *Diskussion.* Verbesserungen in den Gang- und Balancevariablen deuten auf positiven Auswirkungen des Trainings hin. Um diesen Effekt zu bestätigen, wäre für die Zukunft zum einen ein intensiveres Trainingsprogramm empfehlenswert und zum anderen Anpassungen bei der Datenauswertung, um eine bessere Übereinstimmung zwischen den Smartphone-Daten und den Daten der beiden Standard Ganganalyse-Systeme zu erreichen.

# 2 Introduction

Due to the Covid-19 pandemic and the related regulations, like quarantine and social restrictions, there is an increasing demand for settings facilitating the conduction of studies and clinical investigations independent of the physical presence of the respective participants or patients. This could be achieved, for example, by enabling study participation in a home-based setting, e.g. by using wearables as measurement devices for assessing gait and balance. However, these approaches have been applied only recently in the field of motion analyses (Winfried Ilg et al., 2020, Shah et al., 2021) and are not yet part of the standard tools of measuring gait and balance. One wearable device that most persons have at home is a smartphone. Due to its broad availability and the convenient option to implement applications, it represents a hands-on tool for measuring gait and balance in home-based settings.

In the current study, a smartphone was used to measure gait and balance in combination with two common gait analysis systems requiring a laboratory environment: a zebris force plate and an Xsens motion capturing system with inertial sensors. On the smartphone two new applications ("*JuTrack EMA*" and "*JTrack Social"*) have been installed and used for data collection. Both applications were developed at the Research Centre Jülich (Far et al., 2021). JuTrack EMA is used for custom-made questionnaires, so that common clinical questionnaires can be easily implemented into the application. JTrack Social is used for measuring gait with accelerometers and gyrometers, which are routinely embedded in the hardware of each smartphone and allow measuring acceleration and rotation. The use of these two applications should facilitate ease of use, maximize compliance, and minimize the time required to participate in the study. This way of measuring gait and balance was linked to a three-week video-based intervention, which was also performed at home and included twelve gait and balance training sessions of 20 minutes each.

Ideally, this concept can be used in the future for location-independent measurement of gait and balance in participants or patients in a scientific-clinical environment. In combination with video-based training protocols, gait analysis systems optimized for the use at home could facilitate training and testing for e.g. immobile participants, for the elderly or for patients with movement disorders or affective disorders. This is especially important in the light of the current Covid-19 pandemic, which promotes immobility for a variety of reasons and impedes the training that was previously performed in physical presence at various places like physiotherapy practices, fitness centers or in (rehabilitation) hospitals. The present study was a feasibility study of a combined assessment and training protocol for gait and balance in healthy subjects.

The following chapter describes gait and balance characteristics, as well as established and also more recent methods of gait analysis. Furthermore, training methods to improve gait and balance are presented and discussed, and the research objectives of this study are stated.

## 2.1 Physiological Basis of Gait and Balance

Gait as the most basic human way of locomotion can be described in several ways. In a biomechanical kind of view, human gait is split up into several phases referred to as “step” or “stride”. One stride begins with the initial contact of one foot and ends with the initial contact of the same foot (as shown in Fig. 1, blue leg), while a step begins with the initial contact of one foot and ends with the initial contact of the other foot. Two steps therefore correspond to one stride.

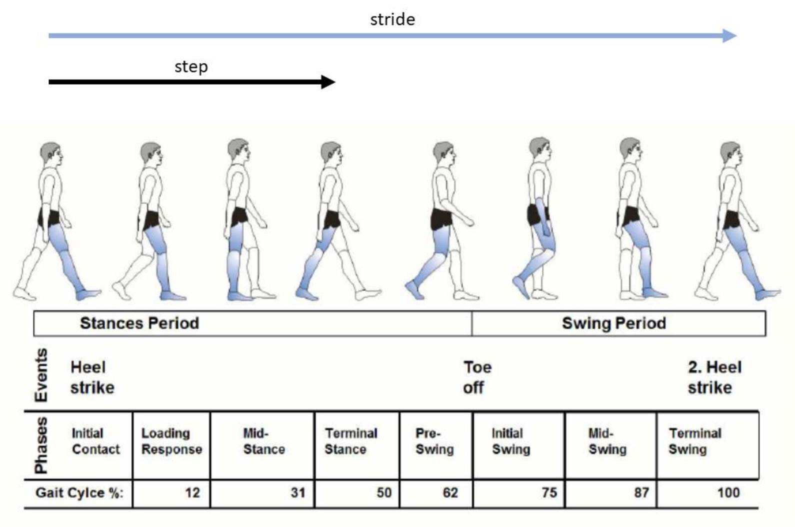



Fig. 1: Visual description of one gait cycle (from: Noraxon MyoPressure Bilateral Gait Report)

During a stride, the leg is in contact with the ground for about two thirds of the stride, and swings during the other third of the stride – these two phases are called stance period and swing period. During these periods, several positions can be defined and used as markers. The three most prominent ones are the Heel Strike, the Mid-Stance and the Toe-Off (Suppa et al., 2020). The most commonly used gait parameters in studies include e.g. stride time (duration of one stride), velocity (mean speed of movement over a defined distance), step width (how far the two feet are apart) and cadence (how many steps are performed within one second). Other variables are often used in addition, but they vary from study to study (e.g. foot rotation, pressure or force values, gait variability, …). The duration of a gait cycle usually remains similar in a person over time (Day & Lord, 2018). In the following table, reference values from two studies with large sample sizes are shown to get a general idea of the range of values. Younger adults usually show a slightly better gait performance compared older adults (e.g. longer step length, higher velocity, Kimura et al., 2007).

| Variables | Asian Men | Asian Women | Older Men | Older Women |
|---|---|---|---|---|
| Stride time (s) | 1.08 | 1.04 | 1.11 | 1.04 |
| Velocity (m/s) | 1.06±0.20 | 1.06±0.19 | 1.32±0.20 | 1.27±0.22 |
| Step width (cm) | 10.74±3.11 | 9.37±2.68 | 9.8±2.5 | 8.3±2.4 |
| Cadence (steps/s) | 1.85±0.17 | 1.92±0.18 | 1.78±0.14 | 1.91±0.18 |

Tab. 1: Reference values for gait variables in male (n=221) and female (n=286) South East Asian adults (mean age 64/60.5 years, age range 21 to ≥81 years, Lau et al., 2020) and in male (n = 705) and female (n = 759) older adults (mean age 73±2.3 years, age range 69 to 80 years, Moe-Nilssen & Helbostad, 2020). Units of the variables were adapted to match units in our study. Step time was calculated from step length and velocity; therefore, no standard deviation is indicated

Various structures of the central nervous system play a crucial role in gait, including the cerebral cortex, thalamus, brainstem structures, basal ganglia and cerebellum (Lewis & Shine, 2016). Among the brainstem structures we find, for example, the central pattern generators (CPG). These neuronal networks are responsible for continuous movements and therefore also for normal gait, as gait is a cyclic and half-automatic movement. These continuous movements do not require continuous activation by descending neurons of the central nervous system after they have been properly activated for the initial step (O'Shea & Weltecke, 2008) and therefore make gait special among other movements. While normal gait is largely automated, other types of gait (e.g. tandem or backward gait) usually acquire additional cognitive processing.

Balance or posture is the ability of keeping the body in the desired position under varying conditions or environments. The balance performance mainly depends on the cerebellum (compensating errors in the execution of movements), the inner ear (detecting movement directions), sensory information from the environment (vision, somatosensation, …) and muscle movements to maintain or to correct a specific position. To prevent falls, postural instability must be identified and corrected.

Gait and balance are impaired in several (neurological) diseases and this can lead to considerable constraints in daily life (e.g. freezing of gait in PD, insecure gait in ataxias). Therefore, the assessment and recognition of these impairments is important in the clinical practice. In the following part, techniques to analyze gait and balance are presented.

## 2.2 Analysis of Gait and Balance

### *2.2.1 Gold Standard of Objective Gait and Balance Analysis*

Observation and description of gait and balance is an easy tool to detect abnormalities in gait and motor performance in people. Analysis of gait and balance begins with very simple methods such as observation and video analysis, which have the advantage of being time and cost efficient. These methods are sufficient to detect abnormal patterns and to subjectively describe gait or balance so that they can be used in clinical routine. However, in more scientific settings, technical devices are preferred to quantify gait or balance and to make the analyses more objective. This can be done in a variety of ways, but among the most commonly used instruments for gait and balance analysis are force plates (pressure-sensitive walkways), body-worn sensor systems (inertial measurement units – IMUs) and video motion capturing systems (Petraglia et al., 2019).

In particular in comparison with data collected from healthy participants, all these systems allow to detect abnormal or altered gait patterns in various disorders like Parkinson’s disease (PD, Ellis et al., 2015), Multiple Sclerosis (MS) or Ataxias (Schmitz-Hübsch et al., 2016). For example, analyses on a force plate (GAITRite™) showed that PD patients had a longer step duration, a shorter step length and greater variability in both, compared to healthy controls (Ellis et al., 2015) and analyses with both a force plate (GAITRite™) and a body-worn sensor system (Mobility Lab™) showed reduced stride length and velocity in ataxia patients (n=12, 3 female, mean age 53, Schmitz-Hübsch et al., 2016). Also, Patterson et al. (2012) showed an association between age and gait velocity in 81 older individuals (43 female, mean age 64.2±22.4 years) in a gait analysis on a force plate (GAITRite™), namely that mean velocity decreased with increasing age, while step length and step time remained equal. The named gait analysis systems are also able to detect performance changes after interventions, for example shown in Conradsson et al. (2015), who assessed gait on a force plate (GAITRite™) before and after a ten-week balance training in PD patients. Participants in the training group (n=47, 19 female, mean age 72.9±6.0 years) showed improved gait velocity and step length in normal gait compared to the control group (n=44, 22 female, mean age 73.6±5.3 years). In a second task, normal gait was combined with a cognitive task, but no improvements were observed after the balance training. Likewise measured with a GAITRite™ walkway, Giardini et al. (2018) showed that two forms of physical exercise training (balance exercises and mobile platform training) improved gait speed in patients with PD. Only the intervention with the balance exercises, however, also led to improvements in cadence and step length.

For balance on the other hand, most studies use center of mass or center of pressure data to determine area of postural sway, path length or mean velocity (Nusseck &

Spahn, 2020, Wan et al., 2021). Higher sway areas and sway velocities can for example be found in young children (Pomarino et al., 2013). In this study, four age groups (2 to 6 years, n=92; 7 to 10 years, n=72; 11 to 20 years, n=93; and 21 to 69 years, n=174) were examined for normal stance on a force plate (zebris FDM-s). The results showed that sway areas and velocities decreased from the youngest to the oldest age group. Although there were not enough participants with older ages to define an older age group, the authors suspected that this effect reverses after a certain age is reached (i.e. above 50 or 60 years). Morenilla et al. (2020) also found altered sway areas and velocities in PD patients (n=25, 10 female, mean age 57.6±11.5) compared to control (n=20, 10 female, mean age 59.1±13.3), when examining normal stance on a force plate (Kistler 9286BA). They found a significant increase in total sway area and in mean anteroposterior and mediolateral displacement for PD patients. Moreover, R. Sun et al. (2018) reported that both their new inertial body-worn sensor (BioStamp) and a force plate (Bertec) were able to discriminate between subjects with severe MS and healthy control. However, the force plate was also able to distinguish between subjects with mild MS and healthy control, as well as between subjects with mild and severe MS, while the inertial sensor was not. Sankarpandi et al. (2017) investigated feasibility of a wearable inertial sensor system (Opal) and showed good within-session and between-session reliability. Additionally, the sway distance measured with the sensor system had the ability to distinguish between fallers and non-fallers. Another study which measured balance with a force plate showed that this measurement tool is able to detect changes in performance after training interventions: Improvements in the sway distance (measured on a zebris force plate) were found for patients with chronic stroke (n=13, 5 female, mean age 57.3±10.5 years), after they participated in a virtual reality reflection therapy (In et al., 2016). The control group did not show any significant improvements in balance performance.

In summary, gold standard gait and balance analysis systems are able to detect differences in gait and balance performance between healthy controls and different age groups or diseases; can distinguish between severities of diseases and can detect shifts in performance over time.

### *2.2.2 Smartphone-based Gait and Balance Analysis*

In recent years several studies have been published that analyze gait with accelerometers in smartphones or similar electronic devices (e.g. iPod touch, Ellis, 2015). These devices include accelerometers and gyroscopes as standard and can be used to determine various gait variables. This has the added advantage that the measurements are closer to real-world activity and thus more likely represent the gait pattern of the participant in daily life. Yamada et al. (2012), for example, used a Sony Ericsson smartphone, attached to the back at the height of L3 with a semi-elastic belt, to measure gait. They found lower walking speed, lower gait balance and higher gait variability in patients with rheumatism (n=39, 35 female, mean age 65.9±10y) and concluded that this method is acceptable for gait assessment and can describe the patients' disease activity. They therefore suggested that smartphone gait analysis could be used as a standard method in the future. Steins et al. (2014) draw similar conclusions for measuring gait with an iPod Touch, compared to an Xsens sensor (gold standard for acceleration) and an optical motion capture system (gold standard for position) in young adults (mean age 26y): The smart device showed reliable temporal gait outcomes (e.g. cadence, step time, walking speed). However, only moderate agreement with the other two systems was found. Ellis et al. (2015) investigated gait variability in PD patients (n=12, 5 female, mean age 65.0±8.4 years) compared to healthy controls (n=12, 4 female, mean age 63.1±7.8 years) with an iPod touch and a force plate (GAITRite™). They found altered gait parameters in both gait analysis systems when walking with rhythmic auditory cueing compared to normal gait and when comparing PD patients to healthy controls. Interestingly, the authors in general found higher values for the iPod comparted to the force plate. Furthermore, Marano et al. (2021) were able to discriminate between fallers and non-fallers in PD patients during lockdown, when using a smartphone application to measure motor tasks, including the 3-m timed-up-and-go test. Out of 15 outcome variables, two were able to discriminate between fallers and non-fallers: The stand-up time and the mediolateral sway in the 3-m timed-up-and-go test.

The applications used in these studies were only used for a specific motor tasks (e.g. normal gait) and are of limited use for other research questions or clinical investigations.

### *2.2.3 Digitalization of Clinical Assessment Tools*

In addition to gait analysis, increasing digitization has been observed in many areas in recent years, e.g. clinical tests and training programs. One example is the SARA score, a widely used clinical scale for assessing and evaluating ataxia, which researchers have adapted so that testing can be easily done at home and help the physician or researcher obtain a more objective assessment. Grobe-Einsler et al. (2021) presented the “SARA home” application which can be downloaded to any tablet or smartphone with a camera and is used to capture day-to-day fluctuations e.g. in gait and stance via video. They found that this assessment can partially replace traditional assessments, but since tracking is not yet automatic, the time required is quite high. Summa et al. (2020) introduced a different approach for the same scale: Their “SaraHome” software is connected to a Microsoft Kinect and a Leap Motion Controller, which recognize 25 joints and hand gestures. This facilitated the collection of results and resulted in high level of interest and participation from both the ten participating children with ataxia and their parents. Initially, however, a considerable amount of effort is required to train both personnel and parents for the use of SaraHome and to create the right set-up for each task. In general, participants showed great interest and satisfaction with the new techniques, which encourages further research in this direction.

Now that different tools for detecting normal and abnormal gait and balance patterns have been described, it remains to be noted that gait and balance performance not only deteriorates with age or certain diseases, but can also be improved by systematic training.

## 2.3 Training Gait and Balance

Gait and balance performance decrease with age, with diseases or with less sportive activity. At the same time, the performance can be increased with appropriate training. Training interventions can differ in terms of where they are carried out, the duration of the intervention, the intensity of the training and, last but not least, the tasks carried out. The following section goes into more detail about the types of gait and balance training used in other studies, the training effects that can be expected, and the advantages and disadvantages of home-based training.

This was shown in several studies. In a study by Perrin et al. (1999), older adults who participated in physical activity and exercise showed improved postural control. W. Ilg et al. (2009) have shown that four weeks of physical therapy plus independent exercise can lead to a reduction in ataxia symptoms (i.e. SARA score) and an improvement in balance (i.e. BBS) in patients with degenerative cerebellar ataxia, when the training is performed three times per week for one hour. W. Sun et al. (2018) also showed that a 16-week intervention of Tai Chi exercises improved postural control and Cadore et al. (2013) summarize a general positive effect of supervised exercise programms on gait performance, balance performance and the reduction of falls. The named studies specifically evaluated supervised training, which is the most common form of training and is well accepted in society. However, if social or personal restrictions make it impossible to take part in a training in presence, other solutions must be found and evaluated in the same manner.

Ellis et al. (2015) suggested in the outlook of their study about smartphone-based gait analysis, to perform a home-based gait training. This is supported by other studies, indicating that practicing at home might be even more important than hospital-based rehabilitation (Miyai et al., 2012), as continuous exercising has the best effects on performance. Therefore, it might be helpful for participants to get in the habit of practicing at home and incorporating exercise into their daily routine if they want to achieve long-term effects on their health and performance. One way to provide training or physical therapy at home is video-based training, either via video conferencing or via offline video recording. Possible advantages of video-based training include lower healthcare costs, better possibilities of quality control and improvement of the content and improved access (e.g. for people with physical disabilities). Possible disadvantages are the lack of a personal relationship and interaction with the therapist/coach and lower acceptance, especially among the older generation (Eriksson et al., 2011). To date, there are few studies that have investigated video-based physical therapy after stroke (Redzuan et al., 2012), shoulder joint replacement (Eriksson et al., 2011), rotator cuff tears (Türkmen et al., 2020), cardiopulmonary diseases (Hwang et al., 2015) and knee problems (Kim et al., 2016; Bini & Mahajan, 2017). The outcome of these studies were similar compared to center-based physical therapy. Eriksson et al. (2011) conducted two months of videoconferencing therapy with older adults after a shoulder joint displacement and reported an overall positive experience. Participants experienced reduced inconvenience (e.g. travel time and costs) and improved independence and motivation to practice. However, in summary, they suggest using these therapy devices as an adjunct to traditional physical therapy. He et al. (2020) conclude in their review about balance and coordination training in degenerative ataxias, that most home-based trainings had positive effects: Although the outcomes were not as good as conventional training, they were still better than baseline and showed positive effects and long-term improvements. Yet, different time periods and training durations have been used in all studies. To the best of our current knowledge, there has been no study examining the effects and motivational aspects of video-based physical therapy for healthy participants of all ages in relation to gait and balance training.

To achieve the best possible outcome from home-based therapy, compliance plays an important role. Compliance can be made measurable by counting repetitions or frequencies of exercises or specific tasks, or by reaching certain recommended levels. Reasons for lack of compliance include that participants may forget to do their exercises, may not want to change their lifestyle, or may be unsure about certain aspects of the training or study (Essery et al., 2017). Nevertheless, there are ways to increase compliance: Essery et al. (2017) suggest that participants should have a positive expectation about of the outcome of the exercise, so the person in charge or physiotherapist should take some time to explain what the exercises are good for and how they can help. In addition, participants should have the opportunity to ask questions, and some may need a reminder to do their exercises. Since social support plays an important role as well, it might be helpful to involve family members or friends, if possible.

## 2.4 Research Question and Aim of the Study

Various studies have been published in which gait and balance performance was investigated either for patients or for older adults before and after a training intervention; or for patients or older adults compared to healthy controls. However, studies are missing which investigate gait and balance performance of healthy adults before and after a home-based training intervention. In this study, healthy adults performed twice a test battery of gait and balance tasks in the gait laboratory and attended a video-based gait and balance training at home in the three weeks interim period. We aimed to

i. investigate the influence of the training on the gait and balance performance and on the individual condition (e.g. self-efficacy, well-being). We hypothesized that an improvement in gait and balance performance, as well as in the questionnaire scores, would occur between the first and second study visit.

ii. evaluate the smartphone app JTrack Social as a gait analysis system for location-independent measurements in comparison with two different standard gait analysis systems (force plate and sensor system). We hypothesized that the data obtained from the smartphone provides sufficiently good quality to achieve a similar rating of the motor performance as the other two systems.

iii. compare the sensitivity of all methods in detecting differences between first and second study visit. We hypothesized that the systems have different profiles for depicting differences.

# 3 Methods

This experimental study included two study visits – at baseline (T1) and at follow-up after four weeks (T2). During each visit, gait and balance tasks were measured using three different gait analysis systems (force plate, motion capturing and smartphone). The two applications JuTrack EMA and JTrack Social were used to answer questionnaires and assess gait. A three-weeks intervention on gait and balance was conducted at home between the two visits. In addition, participants were asked to perform the same gait and balance tasks at home as at T1, measured with the smartphone only. This study was designed as a feasibility study to measure gait and balance and the effect of an intervention in a home-based setting for healthy participants.

| Week | Study visit | Duration | Content | Hardware |
|---|---|---|---|---|
| **0** | T1 (gait lab) | 60min | Questionnaires; gait and balance tasks | Force plate (zebris FDM) |
| | | | | Sensor system (Xsens) |
| | | | | Smartphone (JTrack Social) |
| **1-3** | At home | ca. 10min 1x/week (questionnaires),<br>ca. 10min 1x/week (gait and balance tasks),<br>ca. 20min 4x/week (training) | Questionnaires; gait and balance tasks; training | Smartphone (JTrack Social and JuTrack EMA) |
| **4** | T2 (gait lab) | 60min | Questionnaires; gait and balance tasks | Force plate (zebris FDM) |
| | | | | Sensor system (Xsens) |
| | | | | Smartphone (JTrack Social) |

Tab. 2: Time line for the measurements in the study

## 3.1 Participants

The goal was to recruit at least 25 healthy subjects to participate in this study. This number is based on a power calculation with the software G*Power 3.1.9.7 (Faul et al., 2007), with a one tailed significance of $\alpha = 0.05$, $1-\beta = 0.95$ and a calculated effect size of 0.8 (based on the results of gait speed and cadence in Miyai et al., 2012). The calculation yielded in a number of at least 19 participants, which was increased to 25 to compensate for possible drop-outs. Participation in the study was voluntary and could be terminated at any time. Written informed consent was obtained from all participants. The study was approved by the Ethics Committee of the Heinrich-Heine University in Düsseldorf (Germany) in April 2021.

Inclusion criteria for participants were age between 18 and 75 years, independent and safe gait without a gait aid and availability of an Android-based smartphone with internet access for the duration of the study. Participants should be able to walk a clear distance of about four meters indoors or outdoors without being obstructed (e.g., no need to go around corners, stable ground). Exclusion criteria comprised joint disorders (arthrosis, endoprostheses) or neurological, muscular or other medical disorders that may affect gait, falls within the past year or implanted electronical devices (e.g. pacemaker, deep brain stimulation).

## 3.2 Gait Analysis Systems

The three gait analysis systems used were

a) the zebris FDM *force plate* (4.24m, zebris Medical GmbH, Isny, Germany, https://www.zebris.de/medizin/standanalyse-abrollanalyse-und-ganganalyse-fuer-die-praxis) with the Noraxon® myoPressure software (Noraxon U.S.A., Inc., Arizona, USA, https://www.noraxon.com/our-products/myopressure/),

b) the *Xsens* MVN Awinda system and software (Xsens Technologies B.V., Enschede, Netherlands, https://www.xsens.com/products/mvn-analyze), and

c) individual smartphones of the participants with the app "*JTrack Social*" installed (Biomarker Development , INM-7, Research Centre Jülich, https://play.google.com/store/apps/details?id=inm7.JTrack.JTrack_Social&gl=DE).

An additional app, the *JuTrack EMA* app (Biomarker Development, INM-7, Research Centre Jülich, https://play.google.com/store/apps/details?id=inm7.Jutrack.ema&gl=DE), was used for the retrieval of questionnaires.

In the following, the three different tools will be described briefly.

### *3.2.1 Force Plate – Zebris FDM and MyoPressure*

The zebris FDM is a pressure distribution plate developed for gait analysis. Two FDM2 platforms were combined to achieve a gait track of about 4 meters (4.24m with a sensor area of 4.06m). The zebris FDM uses capacitive pressure sensors to capture the pressure distribution in gait and stance. There were also two cameras connected to the system that recorded a video synchronously with the data recording, which can be used for verification. The myoPressure™ software uses the force and pressure data to create a gait report with pressure prints, center of pressure (COP) parameters, as well as force and duration statistics. This includes for example step time, stride time, cadence, step length, step width, velocity and distribution of gait phases.

The zebris FDM platform is considered as one of the gold standards in gait analyses (e.g. Braun et al., 2015) and is used for a broad variety of gait analyses. For example, Navratilova et al. (2020) tested weather the gait pattern of PD patients changed after deep brain stimulation. Gimunová et al. (2021) studied forward and backward gait in men with and without intellectual disabilities and Suciu et al. (2016) analyzed the effect of a rehabilitation program after ankle surgery.

### *3.2.2 Sensor System – Xsens MVN*

The hardware of the sensor system, the *MVN Awinda* system, consists of 17 wireless motion trackers (sensors) attached to the body with body straps (feet, lower and upper legs, pelvis, sternum, shoulders, upper arms, forearms, hands, head, Schepers et al., 2018). The sensors record angular velocity, acceleration, atmospheric pressure and the earth magnetic field with a frequency of 60 Hz and send this data immediately and wirelessly to the *Awinda Station*, connected to a computer.

The software *MVN Analyze Pro* (V2020.2) was used for live inspection and recording of data. Starting a new session requires entering the subject's body dimensions and calibration. Starting from a neutral position, participants were asked to walk forward, turn around and return to the starting position. The recommended distance of five to ten meters for this purpose was fulfilled in the laboratory environment of this study. This calibration process was repeated until the software indicated the calibration as "good". The avatar then appeared on the computer screen and was visually inspected while the participant walked back and forth for a while. If the participants' gait matched the avatars' gait and the movements looked normal (e.g. no spinning or wiggling body segments), the system was declared ready for analysis.

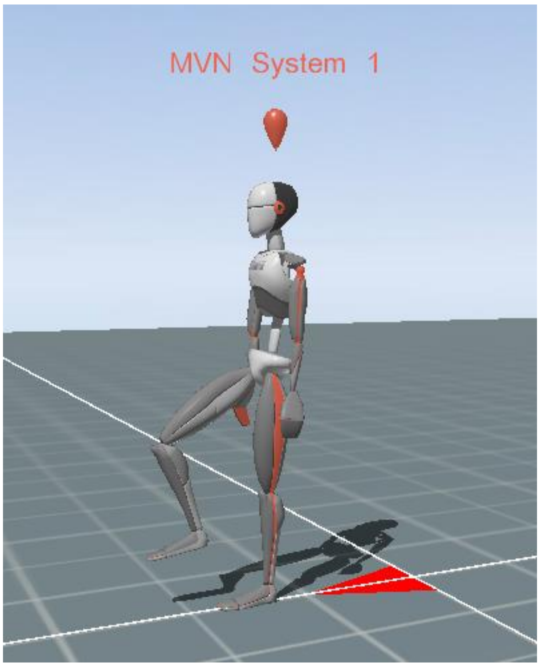



Fig. 2: Screenshot of an MVN avatar in a single leg stance

According to the product information and studies conducted by the manufacturer itself, the Xsens system has a highly accurate time synchronization and is therefore very suitable for measuring human movement (Schepers et al., 2018). The Xsens system is also a common reference system in gait analysis (Khurelbaatar et al., 2015) and produces high accuracy data (Ferrari et al., 2010). Al-Amri et al. (2018) examined 26 healthy participants during functional activities (e.g. walking, jumping) and found high reliability and validity, especially for the lower limbs.

For the evaluation in this study only a subset of the available sensors (feet, pelvis) was used. These sensors are commonly used for the analysis of gait variables (Steins et al., 2014, Shah et al., 2021). A script was used for the extraction of data, which can be found in the supplementary material (see section “7.2 Data extraction Xsens”). All data were visually checked for errors and for plausibility.

### *3.2.3 Smartphone-based Data*

On the smartphone (with an Android operation system), the application JTrack Social had to be downloaded to the device from Google Play Store. The participation in the study was started by scanning a QR-code with the device’s camera, which automatically assigned the participant to random study ID. Participants started the measurement manually in the smartphone app (e.g. typing in “normal gait”) and put the smartphone into their fanny pack during the performance of the tasks. The movement for synchronization was performed before beginning the task and after finishing the task, respectively. After that, the task was stopped manually by clicking on the stop button in the app. During the measurement time, the acceleration and gyroscope data of the smartphone were recorded. A gyroscope is a sensor that measures rotation and thus orientation of a device. The outcome of this sensor is angular velocity. As soon as a connection to the internet was available, the acceleration and gyroscope data of the recorded task was sent to the server automatically for data collection.

The JTrack platform was introduced for remote monitoring in daily life in Far et al. (2021) and has among other indications the function to collect high-frequency raw data from the accelerometer and gyroscope for motion analysis. The app was optimized to deal with different operating systems and pays attention on data privacy and security. As the app is relatively new, studies will follow to prove its quality.

## 3.3 Study Tasks

### *3.3.1 Gait and Balance Tasks in the Laboratory*

For every gait and balance task, the supervisor first started the Xsens software and the Noraxon myoPressure software for recording. The participant had to start the JTrack Social app by opening it and typing in the name of the task to be performed next (e.g. “normal gait”). The time for each task was set to 90s to ensure that the task would be completed on time. Once both participant and the supervisor were ready, the participant pressed the start button and placed the smartphone into a fanny pack provided for the duration of the study. As soon as all devices started recording, the participant first performed a synchronization movement in order to have a start and end mark in all measurement devices. To do so, they lifted their heels into a toe stand and then dropped back down onto their heels. This resulted in a high acceleration in the sensor system and in the smartphone accelerometer, and a high force on the force plate at the same time.

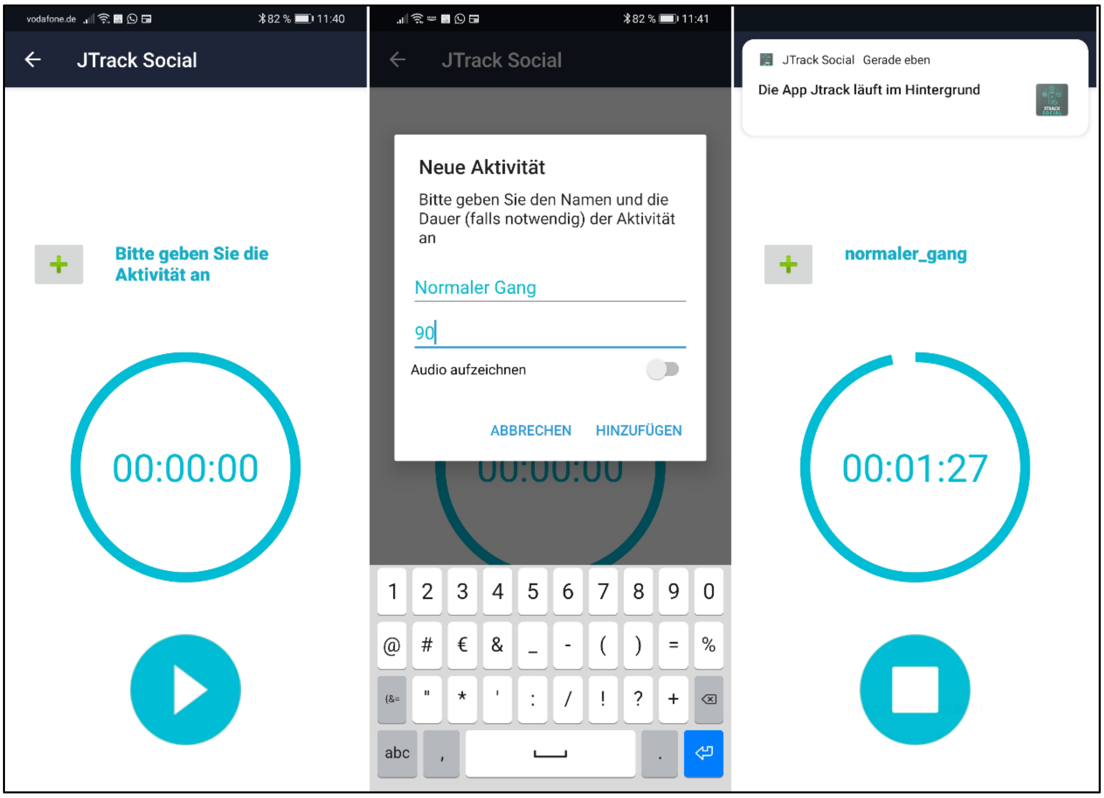



Fig. 3: Example screenshots of the JTrack Social app, i.e. measuring normal gait

The **first** of the tasks in the laboratory was a normal gait over a distance of 4.24m (length of the two zebris force plates). Participants should walk briskly and safely across the force plate, then turn around <u>behind</u> the plate and walk back to the starting position. The task was repeated five times, resulting in a total walking distance of about 40m (10 lanes). In the **second** task, participants walked the same distance backwards. The task was repeated three times, resulting in a total distance of about 24m (6 lanes). The **third** task was a tandem gait. The participants walked in a straight (imaginary) line by placing one foot in front of the other, placing the heel of one foot about a hand's width in front of the toes of the previous foot. At the end of the plate, they turned around and walked back to the starting position. This was repeated twice, resulting in a total distance of about 16m (4 lanes). The **fourth** task was a stance task. The participant placed his/her feet close together and tried to keep the balance as long as possible. The time the participant could remain standing without leaving his/her position or holding up (maximum of 30s) was measured. The **fifth** task was a tandem stance: The participant placed the heel of one foot in front of the toes of the other foot in a line and tried to maintain balance. The participant could choose which foot to place to the front and which one to the back. The time the participant could remain standing without leaving his/her position or holding up (maximum of 30s) was measured. The **sixth** task was similar to the fourth (close stance) with the added difficulty of closing the eyes. Again, the participant tried to maintain balance as good as possible, without leaving his/her position or holding up (maximum of 30s). The **seventh** and final task was a single leg stance, in which the participant tried to maintain balance while standing on one leg. The time the participant could remain standing without leaving his/her position or holding up (maximum of 30s) was measured.

During all tasks and depending on the subjective opinion of the participant, the supervisor closely observed the gait and balance tasks in order to support him/her in case of a stumble or to prevent a fall if necessary.

| Task | Content |
|---|---|
| **Normal gait (NG)** | 10 x 4.24m normal (forward) gait |
| **Backward gait (BG)** | 6 x 4.24m backward gait |
| **Tandem gait (TG)** | 4 x 4.24m gait in tandem gait |
| **Narrow stance (NS)** | Balancing in a narrow stance |
| **Tandem stance (TS)** | Balancing in a tandem stance |
| **Narrow stance with eyes closed (NSEc)** | Balancing in a narrow stance with eyes closed |
| **Single leg stance (SS)** | Balancing on one leg |

Tab. 3: Overview of gait and balance tasks

### *3.3.2 Questionnaires in the Laboratory*

Age, gender, profession and years of education were retrieved in a demographical questionnaire in the laboratory. To assess depression and anxiety, the German versions of the depression module of the patient health questionnaire (PHQ-9, Kroenke et al., 2001, German version: Löwe et al., 2002) and the hospital anxiety and depression scale (Zigmond & Snaith, 1983; German version: HADS-D, Hermann-Lingen et al., 2011) were used. Additionally, general habitual well-being (FAHW, Wydra, 2014) and the self-efficacy, optimism and pessimism (SWOP-K9, Scholler et al., 1999) were assessed. To assess self-efficacy in relation to falls, the (modified) German version of the Activities-Specific Balance Confidence scale was used (ABC-D, Schott, 2008).

The subscores “PHQ_stress” and “PHQ_depression” were selected from the PHQ-9 questionnaire. While the depression variable was used as an exclusion criterion, the stress variable ranged from 0 to 20 and served as a covariate to describe the population. The HADS-D scores also served as exclusion criteria. The anxiety score had a cut-off value of >10 points and the depression score of >8 points. The FAHW score was calculated by subtracting the score of the discomfort questions from the score of the well-being questions. A total score of 38 to 50 or 35 to 47 (men and women, respectively) is defined as “average” by the developers of the questionnaire. Additionally, the score contains a row of smileys, ranging from a happy face to a sad face. This was included in the evaluation by assigning a 1 to the happiest smiley and a 7 to the saddest smiley. The SWOP-K9 questionnaire contains items on self-efficacy (SWOP-SE), optimism (SWOP-OP) and pessimism (SWOP-PS), with scores ranging from 5 to 20, 2 to 8 and 2 to 8, respectively. For the ABC-D questionnaire the scale was adapted to a 4-point response scale (not confident at all, somewhat less confident, somewhat confident, absolutely confident) and a score between 16 (maximum confidence) and 64 (minimum confidence) could be achieved.

### *3.3.3 Gait and Balance Tasks at Home*

Concerning the setting of a gait study, Winfried Ilg et al. (2020) have shown that the variability of gait measurements is increased during unconstrained gait (e.g. outdoors, on a walk) compared to gait in the laboratory. In our study, we used two conditions for gait measurement: on the one hand, a supervised situation in the laboratory and, on the other hand, a non-supervised, home-based situation, but under conditions as similar as possible to those in the laboratory. This was attempted by defining the distance that the participants had to walk using a string that was the same length as the force plates in the laboratory (4.24m).

The same tasks as in section "3.3.1 Gait and Balance Tasks in the Laboratory" were repeated weekly at home. For this purpose, the participants received a list with all tasks in the above-mentioned order and with a task description. The tasks were measured using only the smartphone. Participants started the measurement manually in the JTrack Social app and put the smartphone into the fanny pack while performing the tasks. The movement for synchronization was performed before beginning the task and after finishing the task, respectively. After that, the task was stopped manually by clicking on the stop button in the app. In this thesis, however, only the data from the laboratory environment was evaluated, since too many values were missing in the data from the home-based environment.

### *3.3.4 Questionnaires at Home*

Some of the questionnaires obtained in the gait lab (see section "3.3.2 Questionnaires in the Laboratory") were retrieved weekly via the app *JuTrack EMA*. These were the SWOP-K9 and the ABC-D questionnaire, and a short version of the FAHW questionnaire (FAHW-12), containing 12 of the 42 items of the original version tested at T1 and T2. The questionnaires appeared at the smartphone every 7 days, i.e., after the completion of each week of the intervention.

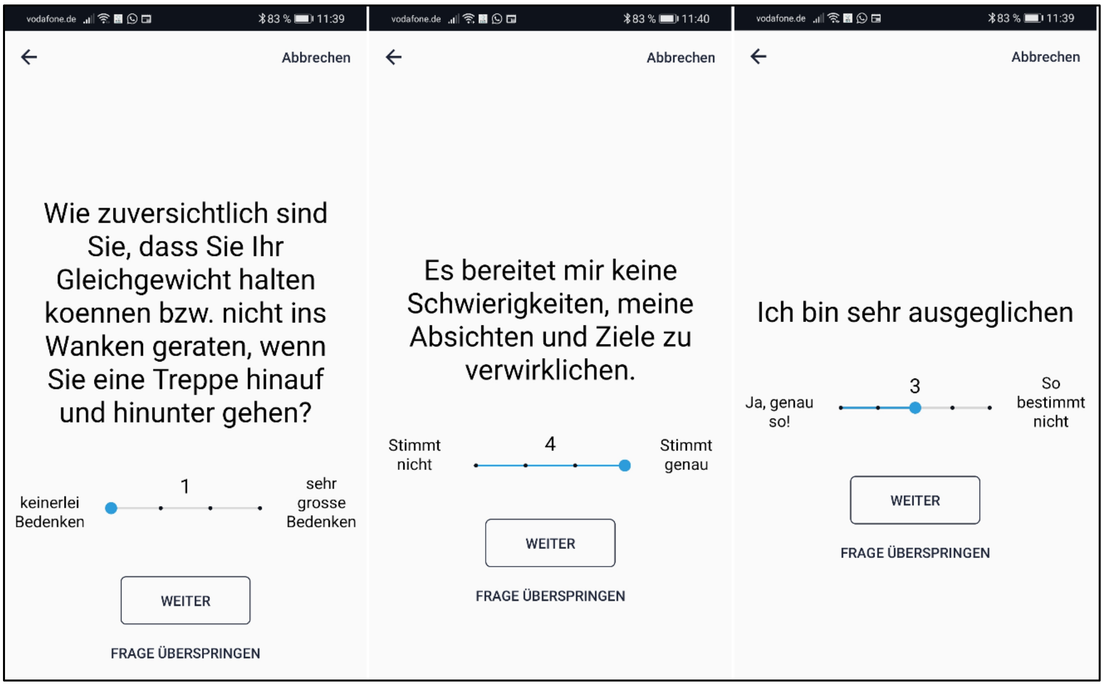



Fig. 4: Example screenshots of the JuTrack EMA app from the ABC-D questionnaire (left), the SWOP-K9 questionnaire (middle) and the FAHW-12 questionnaire (right)

### 3.3.5 *Training at Home*

Gait and balance training was performed four times per week for 20 minutes in the form of videos, that were uploaded to a server. The videos were produced by a physical therapy practice (PhysioStützpunkt, Köln, Germany) and show a physiotherapist, explaining and demonstrating various tasks to improve gait and balance. This included strength training, coordination training, stability training and mobility. The twelve videos progressed from simple to more demanding tasks and also included ideas on how to make certain tasks easier or more challenging if needed. Videos could be paused or repeated at any time, but participants were instructed to perform each training session only once until their second study visit was completed. Afterwards, access to the videos was maintained for a few weeks so that they could repeat some units and benefit from the training. The training protocol is given in detail in the supplementary material (see “7.1 Training Protocol”).

## 3.4 Statistics

From a set of variables that have been extracted for the gait tasks in each gait analysis system, three were selected that were consistently available across all systems: *Gait velocity* (average velocity across all straight distances covered in the task, measured in meters per second), *stride time* (average duration of one stride or two consecutive steps in seconds) and *cadence* (average number of steps that are performed within one second). Additionally, *step width* was extracted from the myoPressure™ gait report and from the sensor data, as this is an important variable to detect abnormal gait patterns (e.g. broadened base of support in cerebellar ataxias, see Nonnekes et al., 2018). However, the step width cannot be estimated – or only imprecisely –from the acceleration data of the smartphone and was therefore not extracted from JuTrack Social. For the balance tasks, the center of mass *(COM) sway area* (area of an ellipse enclosing all data points in x- and y-direction) and the *velocity of the COM* (average distance in millimeters that the participant travelled per second) were chosen. These two variables have shown good reliability in other studies (e.g. Terra et al., 2020, Kouvelioti et al., 2015) and are commonly used for examining balance performance (Wan et al., 2021, Pomarino et al., 2013, Nusseck & Spahn, 2020). Both variables were available for all three gait analysis systems.

| | Output variable | Description |
|---|---|---|
| **Gait** | Stride time | Time to complete one stride (two steps) in seconds |
| | Cadence | Number of steps per second |
| | Velocity | Speed of movement in meters per second |
| | Step width* | Lateral distance of left and right foot at one step |
| **Balance** | COM ellipse area | Ellipse, enclosing 95% of all data points (or all, in the sensor system) during a stance task in square millimeter (mediolateral and anteroposterior displacement) |
| | COM velocity | Speed of movement during a stance task in millimeters per second (mediolateral and anteroposterior displacement) |

Tab. 4: Overview of gait and balance variables of all gait analysis systems used for statistical analysis. * not obtained with the smartphone

Before performing further tests, the variables were checked for normal distribution using quantile-quantile plots (QQ-plots), which should follow a 45-degree line if both samples come from the same distribution, and the Kolmogorov-Smirnov statistical test, which is very sensitive to small deviations from the normal distribution. For testing this assumption, a significance level of $\alpha=5\%$ was chosen.

To analyze changes over time between the questionnaire scores at the first and second study visit (T1 and T2), either an ordinary paired-sample t-test was performed if the data scores were normally distributed, or a Wilcoxon rank test, if the data were not normally distributed. To analyze changes over time of the one variable within one gait analysis system, a one-way repeated measures MANOVA (multivariate analysis of variance) was performed. If the results were statistically significant (Wilks' Lambda $p<0.05$), post-hoc tests at a univariate level were performed to detect where the differences can be found. Correlations between the questionnaire scores, between the individual variables <u>within one</u> gait analysis system, and between variables in <u>all</u> gait analysis systems, were calculated with the Pearson correlation coefficient ($\alpha=5\%$), if the majority of variables were normally distributed. In this context, a correlation between 0 and 0.09 was described as negligible, 0.10 to 0.39 as weak, 0.40 to 0.69 as moderate, 0.70 to 0.89 as strong and 0.90 to 1.00 as very strong.

Boxplots of all gait and balance variables were checked and extreme outliers were excluded (>3*SD).

Analyses were performed in line with recommendations of the statistical mentoring of the Heinrich-Heine university Düsseldorf.

# 4 Results

A total of 25 participants with an average age of 44 years (±18.4 years) took part in the first study visit (T1, 52% female, 92% right-handed). One participant had missing data from the sensor system due to technical problems.

For the second study visit, there was a drop-out of four participants (injury independent of the study (1), technical difficulties (1) and time problems (2)). This led to a sample of 21 participants at T2 with an average age of 44.7±19.4 years (57% female, 95% right-handed).

## 4.1 Demographic Variables and Questionnaire Scores

QQ-plots showed a normal distribution for all demographic variables and questionnaire scores except the ABC-D score at both study visits. This was confirmed by a Kolmogorov-Smirnov test, showing that the two ABC-D scores are not normally distributed ($p<0.0005$ for both tests). An overview of all applied questionnaires is given in section 3.3.2 “Questionnaires in the Laboratory”. Because one participant showed a depressive mood (score 10), all analyses were conducted with and without this subject. Since results did not differ greatly, data from this participant were not excluded from further analyses.

| | Min. | Max. | Mean | SD |
|---|---|---|---|---|
| **Age (years)** | 20 | 71 | 44.08 | 18.369 |
| **Education (years)** | 10 | 25 | 15.20 | 3.202 |
| **HADS-D Anxiety (score)** | 0 | 9 | 3.32 | 2.780 |
| **HADS-D Depression (score)** | 0 | 10 | 2.64 | 2.612 |
| **PHQ Stress (score)** | 0 | 8 | 2.80 | 2.141 |

Tab. 5: Demographic information of all participants (n=25). Education includes school years (e.g. German Abitur equals 12 years of education). The HADS-D anxiety score has a cut-off value of >10 and the HADS-D depression score has a cut-off value of >8. The PHQ stress score has a maximum of 20 points

To test for differences between the questionnaires obtained at both study visits, a t-test was performed for all variables except for the ABC-D test. The t-test revealed no significant differences for any on the tested variables ($p>0.09$). For the ABC-D test, a Wilcoxon rank test was performed, which also showed no significant differences between the two measurement points ($p=0.927$).

| | T1 | | | | T2 | | | |
|---|---|---|---|---|---|---|---|---|
| | Min. | Max. | Mean | SD | Min. | Max. | Mean | SD |
| **SWOP-SE (score)** | 2.0 | 3.8 | 3.080 | 0.49 | 2.2 | 4.0 | 3.229 | 0.4485 |
| **SWOP-OP (score)** | 2.0 | 4.0 | 3.240 | 0.631 | 1.5 | 4.0 | 3.119 | 0.7891 |
| **SWOP-PS (score)** | 1.0 | 3.0 | 1.740 | 0.614 | 1.0 | 3.0 | 1.667 | 0.7130 |
| **ABC-D (score)** | 16 | 28 | 17.96 | 2.574 | 16 | 24 | 17.76 | 2.343 |
| **FAHW (score)** | 21 | 83 | 59.12 | 16.821 | -5 | 86 | 54.55 | 25.310 |
| **FAHW Smilie (score)** | 1 | 3 | 2.04 | 0.611 | 1 | 4 | 2.25 | 0.786 |

Tab. 6: Descriptive statistics of the questionnaire scores at the first and second study visit (T1 and T2, n=21). SE = self-efficacy (possible range: 5 to 20), OP = optimism (possible range: 2 to 8), PS = pessimism (possible range: 2 to 8). Activities-Specific Balance Confidence scale (ABC-D, possible range: 16 to 64), general habitual well-being (FAHW, average reference values between 35 and 50, smiley score ranging from 1 to 7) Significant differences in mean are indicated by bold font.

The demographic characteristics (age, gender, handedness and years of education) did not correlate significantly with each other and with any of the questionnaire scores. However, the questionnaire scores had several significant correlations with each other, which are shown in Tab. 7. A strong negative correlation was found between the general habitual well-being and the depression score (better well-being with less depressive mood), while negligible to moderate correlations were found between the activities-specific balance confidence scale and the other, more psychological, scores.

| | | HADS-D depression | PHQ stress | SWOP-SE | SWOP-OP | ABC-D | FAHW | FAHW_smiley |
|---|---|---|---|---|---|---|---|---|
| **HADS-D anxiety** | Cor | **0.608**** | 0.291 | **-0.436*** | -0.295 | 0.212 | **-0.676**** | **0.532**** |
| | Sign. | 0.001 | 0.158 | 0.029 | 0.152 | 0.310 | 0.000 | 0.006 |
| **HADS-D depression** | Cor. | | **0.486*** | -0.348 | **-0.565**** | 0.215 | **-0.848**** | **0.453*** |
| | Sign. | | 0.014 | 0.089 | 0.003 | 0.303 | 0.000 | 0.023 |
| **PHQ stress** | Cor. | | | -0.365 | **-0.410*** | **0.543**** | **-0.662**** | **0.484*** |
| | Sign. | | | 0.072 | 0.042 | 0.005 | 0.000 | 0.014 |
| **SWOP-SE** | Cor. | | | | 0.313 | -0.315 | **0.425*** | -0.150 |
| | Sign. | | | | 0.128 | 0.126 | 0.034 | 0.473 |
| **SWOP-OP** | Cor. | | | | | 0.045 | **0.541**** | **-0.458*** |
| | Sign. | | | | | 0.832 | 0.005 | 0.021 |
| **FAHW** | Cor. | | | | | | | **-0.596**** |
| | Sign. | | | | | | | 0.002 |

Tab. 7: Overview of correlation between the questionnaire scores (after Pearson, n=25, *p<0.05, **p<0.01). Questionnaires from the first study visit T1 are used. Rows and columns without any significant results were removed from the table in order to have a better overview. Cor. = correlation after Pearson, Sign. = significance (two-tailed). SE = self-efficacy, OP = optimism.

## 4.2 Gait and Balance Performance

Among the gait and balance variables, 32 out of 114 gait and balance variables of all three systems together did not have a normal distribution according to q-q-plots. However, a Kolmogorov-Smirnov test revealed 52 variables that were not normally distributed. Since this still affected only the minority of variables, parametric tests were chosen for further analysis of all variables. As a control, the correlation plots were examined for outliers and Spearman correlations were also calculated. No obvious differences were observed.

Boxplots of all gait and balance variables were checked and extreme outliers were excluded (>3*SD). This affected eight values in the force plate data, 14 values in the sensor system and 12 values in the smartphone data.

## Gait Performance

In Tab. 8, values of all gait variables are displayed before training (T1) and after training (T2) for all three systems. Significant differences were found in all variables within normal gait (force plate), in two variables within normal gait and three variables within tandem gait (sensor system), and one variable within backward gait (smartphone app). Significant differences within the post-hoc test were additionally found for two variables within backward gait (force plate) and one variable within backward gait (sensor system).

| | | | T1 | | | | | T2 | | | | | p | Δ % |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | N | Min. | Max. | Mean | SD | N | Min. | Max. | Mean | SD | | |
| **Force plate** | Normal gait | **stride time [s]** | 25 | 0.97 | 1.55 | **1.20** | 0.13 | 20 | 0.91 | 1.29 | **1.13** | 0.10 | **0.003** | **-6.15** |
| | | **Cadence [steps/s]** | 25 | 1.30 | 2.08 | **1.70** | 0.17 | 20 | 1.55 | 2.20 | **1.80** | 0.18 | **0.002** | **+5.89** |
| | | **Velocity [m/s]** | 25 | 0.64 | 1.28 | **0.98** | 0.14 | 20 | 0.92 | 1.42 | **1.09** | 0.12 | **0.002** | **+11.01** |
| | | **step width [cm]** | 25 | 7 | 16 | **11.64** | 2.60 | 20 | 7 | 15 | **10.65** | 2.50 | **0.002** | **-8.51** |
| | Backward gait | *stride time [s]* | 25 | 1.04 | 1.56 | *1.22* | 0.13 | 20 | 0.94 | 1.37 | *1.17* | 0.12 | *0.027* | *-4.01* |
| | | Cadence [steps/s] | 25 | 1.32 | 1.92 | 1.66 | 0.16 | 20 | 1.47 | 2.12 | 1.73 | 0.18 | 0.760 | +4.24 |
| | | *Velocity [m/s]* | 25 | 0.53 | 0.86 | *0.69* | 0.09 | 20 | 0.61 | 0.92 | *0.76* | 0.09 | *0.028* | *+9.43* |
| | | step width [cm] | 25 | 10 | 24 | 18.08 | 3.19 | 20 | 12 | 24 | 17.45 | 3.20 | 0.886 | -3.48 |
| | Tandem gait | stride time [s] | 20 | 1.19 | 2.44 | 1.66 | 0.31 | 19 | 1.00 | 2.44 | 1.61 | 0.35 | 0.263 | -2.93 |
| | | Cadence [steps/s] | 21 | 0.68 | 1.68 | 1.23 | 0.24 | 19 | 0.85 | 2.02 | 1.33 | 0.26 | 0.064 | +8.59 |
| | | Velocity [m/s] | 21 | 0.22 | 0.72 | 0.45 | 0.12 | 18 | 0.25 | 0.83 | 0.49 | 0.13 | 0.080 | +7.81 |
| | | step width [cm] | 21 | 1 | 5 | 2.24 | 1.04 | 19 | 1 | 4 | 2.00 | 0.94 | 0.414 | -10.71 |
| **Sensor system** | Normal gait | **stride time [s]** | 24 | 0.94 | 1.51 | **1.18** | 0.13 | 21 | 0.93 | 1.28 | **1.11** | 0.10 | **0.003** | **-6.36** |
| | | **Cadence [steps/s]** | 24 | 1.32 | 2.13 | **1.71** | 0.18 | 21 | 1.56 | 2.14 | **1.82** | 0.17 | **0.001** | **+6.42** |
| | | Velocity [m/s] | 24 | 0.59 | 1.27 | 0.97 | 0.15 | 21 | 0.65 | 1.39 | 1.03 | 0.17 | 0.071 | +6.48 |
| | | step width [cm] | 24 | 5.30 | 15.99 | 10.60 | 3.42 | 21 | 1.88 | 16.83 | 9.27 | 3.48 | 0.266 | -12.50 |

| | | | T1 | | | | | T2 | | | | | p | Δ % |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | **N** | **Min.** | **Max.** | **Mean** | **SD** | **N** | **Min.** | **Max.** | **Mean** | **SD** | | |
| **Sensor system** | Backward gait | stride time [s] | 24 | 1.03 | 1.46 | 1.21 | 0.11 | 21 | 0.94 | 1.35 | 1.16 | 0.11 | 0.073 | -4.45 |
| | | Cadence [steps/s] | 24 | 1.37 | 1.95 | 1.66 | 0.15 | 21 | 1.48 | 2.14 | 1.74 | 0.18 | 0.074 | +4.79 |
| | | *Velocity [m/s]* | 24 | 0.31 | 0.84 | *0.66* | 0.12 | 21 | 0.58 | 0.89 | *0.75* | 0.10 | *0.007* | *+13.91* |
| | | step width [cm] | 24 | 6.24 | 19.67 | 11.86 | 3.40 | 21 | 2.45 | 17.88 | 11.53 | 3.70 | 0.676 | -2.79 |
| | Tandem gait | **stride time [s]** | 24 | 1.17 | 3.11 | **1.76** | 0.42 | 21 | 1.00 | 1.96 | **1.49** | 0.23 | **0.006** | **-15.33** |
| | | **Cadence [steps/s]** | 24 | 0.64 | 1.70 | **1.19** | 0.25 | 20 | 1.02 | 1.69 | **1.35** | 0.18 | **0.002** | **+12.72** |
| | | **Velocity [m/s]** | 24 | 0.15 | 0.98 | **0.40** | 0.17 | 20 | 0.19 | 0.80 | **0.44** | 0.13 | **0.044** | **+10.28** |
| | | step width [cm] | 22 | 0.72 | 5.67 | 2.44 | 1.06 | 21 | 0.81 | 7.48 | 2.84 | 1.73 | 0.545 | +16.10 |
| **Smartphone** | Normal gait | stride time [s] | 17 | 1.10 | 1.51 | 1.23 | 0.09 | 15 | 1.03 | 1.50 | 1.21 | 0.14 | 0.423 | -1.67 |
| | | Cadence [steps/s] | 18 | 1.31 | 1.83 | 1.63 | 0.14 | 15 | 1.34 | 1.95 | 1.70 | 0.18 | 0.157 | +4.06 |
| | | Velocity [m/s] | 18 | 0.27 | 0.37 | 0.32 | 0.03 | 15 | 0.26 | 0.42 | 0.33 | 0.05 | 0.275 | +1.99 |
| | Backward gait | stride time [s] | 19 | 1.14 | 1.32 | 1.22 | 0.05 | 11 | 1.05 | 1.52 | 1.20 | 0.13 | 0.453 | -1.35 |
| | | Cadence [steps/s] | 19 | 1.52 | 1.79 | 1.65 | 0.07 | 11 | 1.33 | 1.92 | 1.69 | 0.17 | 0.277 | +2.46 |
| | | **Velocity [m/s]** | 19 | 0.22 | 0.37 | **0.30** | 0.04 | 11 | 0.27 | 0.40 | **0.31** | 0.04 | **0.005** | **+4.15** |
| | Tandem gait | stride time [s] | 19 | 1.08 | 1.57 | 1.29 | 0.10 | 13 | 1.10 | 1.46 | 1.26 | 0.11 | 0.561 | -2.66 |
| | | Cadence [steps/s] | 19 | 1.29 | 1.78 | 1.57 | 0.12 | 13 | 1.39 | 1.87 | 1.62 | 0.15 | 0.885 | +2.90 |
| | | Velocity [m/s] | 19 | 0.20 | 0.31 | 0.23 | 0.03 | 13 | 0.19 | 0.34 | 0.26 | 0.05 | 0.742 | +11.69 |

Tab. 8: Differences in mean between the first (T1) and second study visit (T2) for the gait variables of all three gait analysis systems. The percentage change is indicated in "Δ %". Bold font indicates a significant difference in time (T1-T2, $p<0.05$) and italic font indicates a difference in time in the post-hoc test only ($p<0.05$). Min. = minimum, max. = maximum, SD = standard deviation

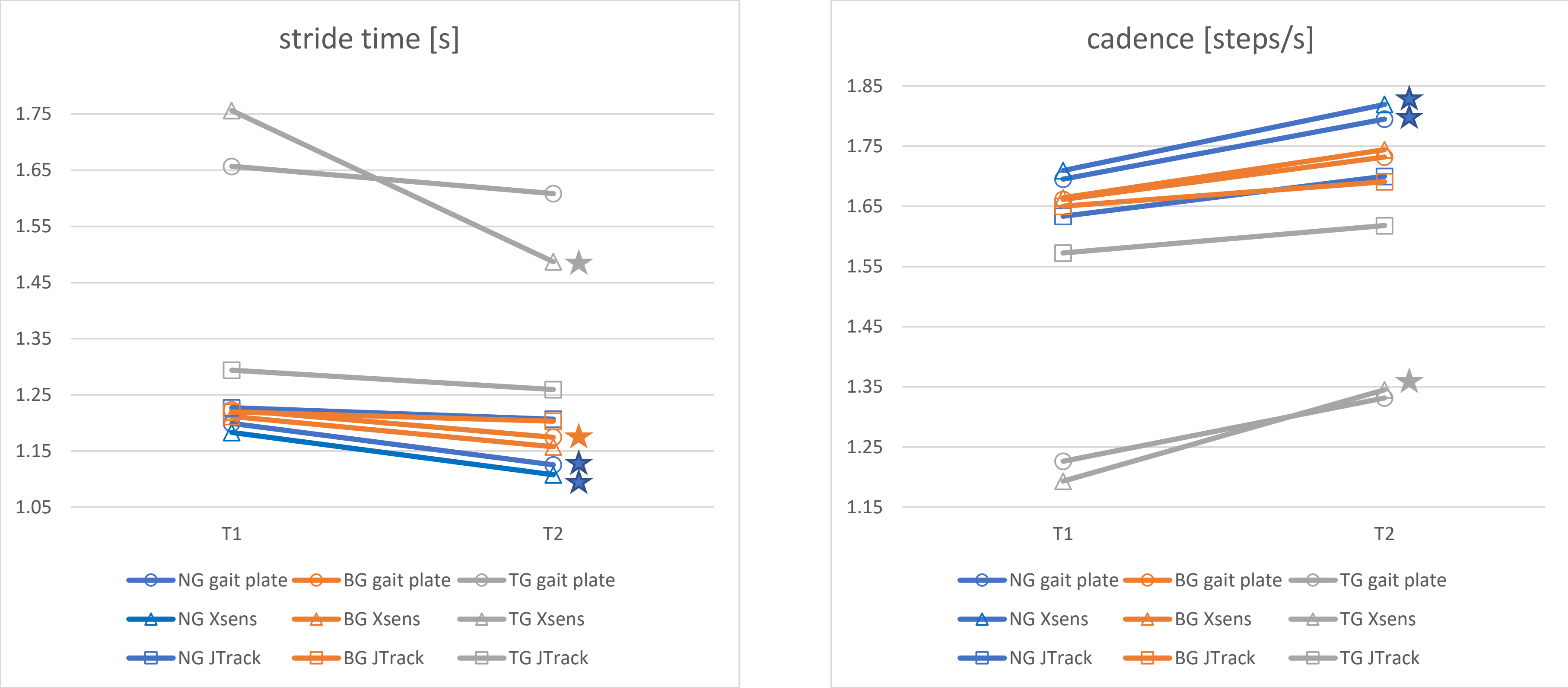



Fig. 5: Graphical representation of the mean values of stride time and cadence for all three gait analysis systems at T1 and T2 (before and after training). Significant differences in time are highlighted by an asterisk. BG = backward gait, NG = normal gait, TG = tandem gait

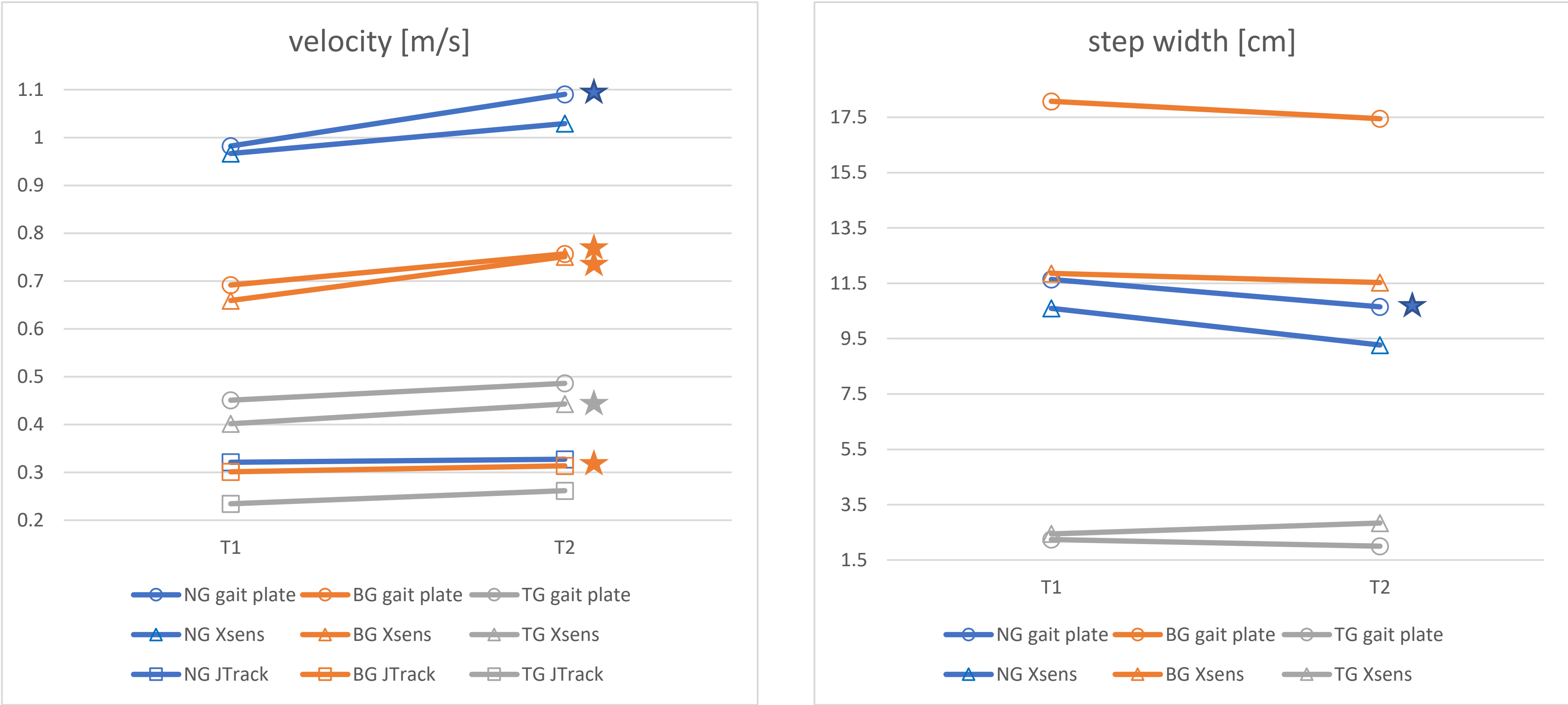



Fig. 6: Graphical representation of the mean values of velocity and step width for all three gait analysis systems at T1 and T2 (before and after training). Significant differences in time are highlighted by an asterisk. BG = backward gait, NG = normal gait, TG = tandem gait

**Balance Performance**

Significant differences between balance variables measured at the first and second study visit were less frequent than between gait variables. Significant differences were present for the COM velocity in the tandem stance of the force plate, and for the COM velocity in the narrow stance and the COM ellipse area in the single leg stance of the smartphone app.

| | | | T1 | | | | | T2 | | | | | p | Δ % |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | N | Min. | Max. | Mean | SD | N | Min. | Max. | Mean | SD | | |
| Force plate | NS | COM ellipse [mm²] | 25 | 206.0 | 1439.0 | 719.92 | 307.54 | 20 | 256.0 | 1826.0 | 688.30 | 352.60 | 0.492 | -4.39 |
| | | COM velocity [mm/s] | 25 | 9.0 | 23.0 | 15.60 | 4.02 | 20 | 8.0 | 31.0 | 16.30 | 5.30 | 0.744 | +4.49 |
| | **TS** | COM ellipse [mm²] | 25 | 336.0 | 3348.0 | 1430.44 | 853.08 | 19 | 227.0 | 2314.0 | 1075.21 | 594.77 | 0.219 | -24.83 |
| | | **COM velocity [mm/s]** | 24 | 28.0 | 107.0 | **52.33** | 17.93 | 20 | 22.0 | 135.0 | **50.15** | 29.78 | **0.006** | **-4.17** |
| | NSEc | COM ellipse [mm²] | 24 | 296.0 | 1622.0 | 981.33 | 366.76 | 20 | 345.0 | 1730.0 | 960.10 | 400.45 | 0.630 | -2.16 |
| | | COM velocity [mm/s] | 25 | 11.0 | 42.0 | 27.64 | 7.48 | 20 | 12.0 | 48.0 | 25.60 | 8.52 | 0.094 | -7.38 |
| | SS | COM ellipse [mm²] | 20 | 439.0 | 1255.0 | 878.05 | 221.37 | 20 | 394.0 | 2345.0 | 977.80 | 447.48 | 0.807 | +11.36 |
| | | COM velocity [mm/s] | 24 | 24.0 | 111.0 | 53.63 | 26.48 | 20 | 22.0 | 109.0 | 47.85 | 21.84 | 0.261 | -10.78 |
| Sensor system | NS | COM ellipse [mm²] | 24 | 312.2 | 3628.9 | 1521.86 | 772.73 | 21 | 522.4 | 3527.5 | 1358.79 | 727.22 | 0.263 | -10.72 |
| | | COM velocity [mm/s] | 24 | 4.76 | 10.48 | 6.58 | 1.53 | 20 | 3.7 | 10.1 | 6.44 | 1.48 | 0.835 | -2.13 |
| | TS | COM ellipse [mm²] | 23 | 263.6 | 4095.1 | 1515.35 | 948.28 | 20 | 376.2 | 2609.4 | 1397.48 | 681.17 | 0.732 | -7.78 |
| | | COM velocity [mm/s] | 22 | 5.1 | 11.6 | 8.55 | 1.81 | 21 | 4.4 | 19.3 | 9.32 | 3.77 | 0.732 | +9.01 |
| | NSEc | COM ellipse [mm²] | 23 | 754.3 | 3138.0 | 1730.55 | 655.97 | 21 | 528.7 | 3467.2 | 1542.95 | 829.00 | 0.201 | -10.84 |
| | | COM velocity [mm/s] | 24 | 5.47 | 16.37 | 8.72 | 2.41 | 21 | 3.9 | 11.4 | 7.76 | 2.03 | 0.075 | -11.01 |
| | SS | COM ellipse [mm²] | 20 | 466.0 | 15835.0 | 3859.69 | 3862.79 | 18 | 434.8 | 10074.4 | 2710.43 | 2320.89 | 0.750 | -29.78 |
| | | COM velocity [mm/s] | 21 | 6.6 | 28.9 | 13.07 | 6.45 | 20 | 6.4 | 21.9 | 11.85 | 4.17 | 0.445 | -9.33 |

| | | | T1 | | | | | T2 | | | | | p | Δ % |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | N | Min. | Max. | Mean | SD | N | Min. | Max. | Mean | SD | | |
| **Smartphone** | NS | COM ellipse [mm²] | 17 | 119.3 | 4351.5 | 1481.48 | 1216.17 | 14 | 49.2 | 5224.1 | 1779.94 | 1594.56 | 0.824 | +20.15 |
| | | **COM velocity [mm/s]** | 18 | 3.2 | 24.8 | **16.26** | 6.16 | 14 | 5.9 | 24.0 | **15.52** | 6.33 | **0.047** | **-4.55** |
| | TS | COM ellipse [mm²] | 16 | 0.6 | 13516.3 | 2512.69 | 3407.80 | 11 | 304.9 | 18644.7 | 4159.06 | 5362.40 | 0.874 | +65.52 |
| | | COM velocity [mm/s] | 17 | 1.0 | 24.7 | 16.97 | 6.04 | 13 | 1.5 | 41.1 | 20.30 | 10.99 | 0.655 | +19.62 |
| | NSEc | COM ellipse [mm²] | 14 | 94.7 | 4406.3 | 1466.86 | 1155.15 | 12 | 56.7 | 7299.2 | 3047.98 | 2413.53 | 0.202 | +107.79 |
| | | COM velocity [mm/s] | 16 | 9.7 | 24.3 | 16.92 | 4.50 | 12 | 7.7 | 24.0 | 16.93 | 5.14 | 0.893 | +0.06 |
| | SS | **COM ellipse [mm²]** | 14 | 0.8 | 3171.3 | **1841.74** | 1244.78 | 11 | 88.2 | 3111.2 | **1252.32** | 834.00 | **0.028** | **-32.00** |
| | | COM velocity [mm/s] | 16 | 0.9 | 32.6 | 16.86 | 8.95 | 12 | 8.1 | 22.9 | 17.78 | 4.44 | 0.894 | +5.46 |

Tab. 9: Differences in mean between the first (T1) and second study visit (T2) for the balance variables of all three gait analysis systems Bold font indicates a significant difference in time (T1-T2, $p<0.05$) and italic font indicates a difference in time in the post-hoc test only ($p<0.05$). COM = center of mass, min. = minimum, max. = maximum, NS = narrow stance, NSEc = narrow stance with eyes closed, SD = standard deviation, SS = single leg stance, TS = tandem stance

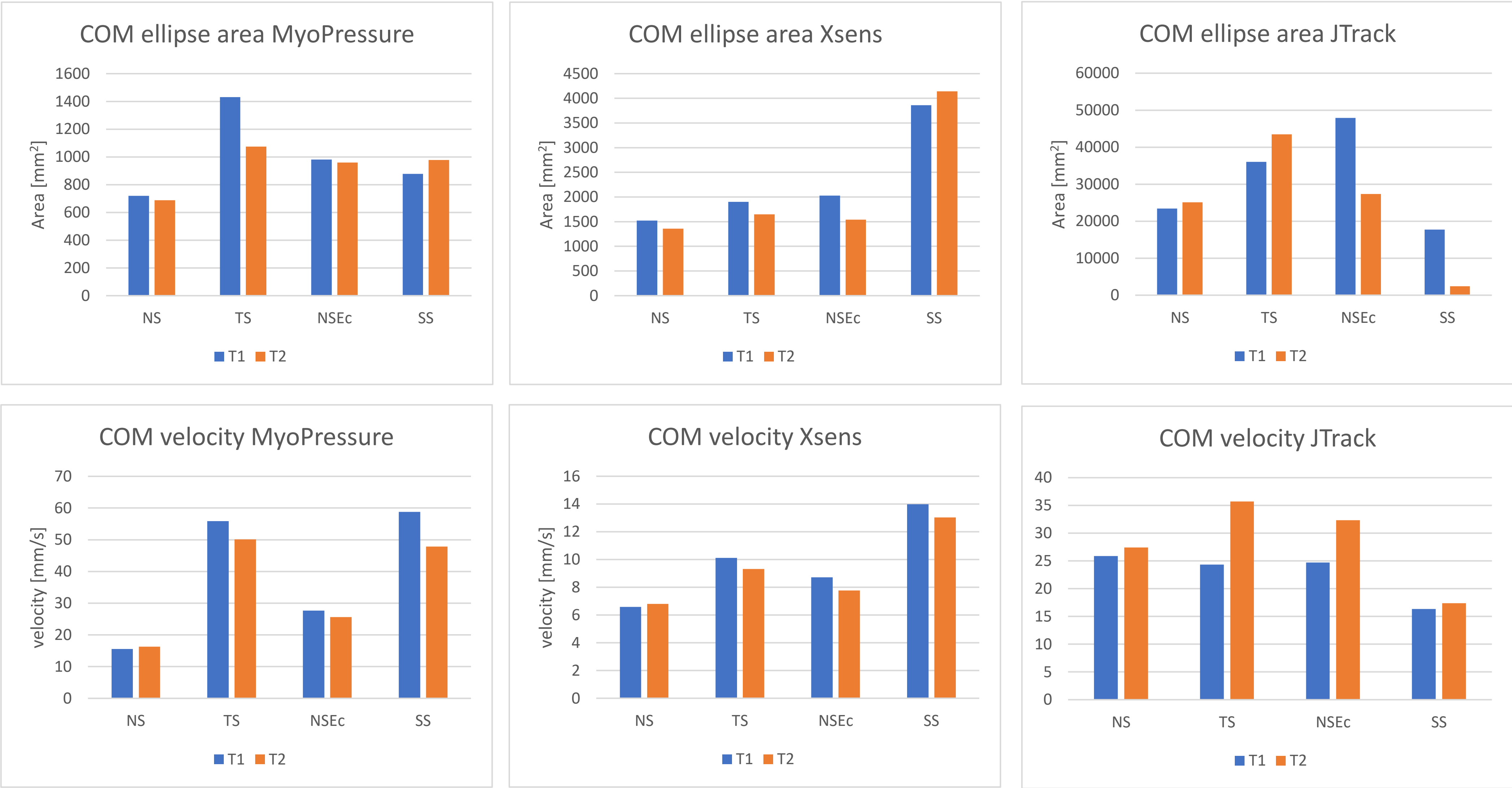



Fig. 7: Graphical overview over the balance variables (center of mass ellipse area and velocity) in all three gait analysis systems at both measurement points (first measurement, T1, second measurement, T2).

### *4.2.1 Differences Over Time – Force Plate*

For the normal gait an effect of time was found (p = 0.007). The post-hoc tests revealed that there was a significant difference in time for all analyzed variables: stride time (p = 0.003), cadence (p = 0.002), velocity (p = 0.002), and step width (p = 0.002). For the backward gait, no significant effect of time was found (p = 0.303). However, post hoc tests showed a significant difference in two of the variables, that is, stride time (p = 0.027) and velocity (p = 0.028). For the tandem gait, no significant effect of time was found (p = 0.291).

For the tandem stance, an effect of time was found (p = 0.014). Post hoc tests showed a significant difference for the speed of movement in the tandem stance (p = 0.003). Contrary, for the narrow stance, narrow stance with eyes closed and the single leg stance, no significant effect of time was found (p = 0.491, p = 0.221 and p = 0.259, respectively).

### *4.2.2 Differences Over Time – Sensor System*

In contrast to the force plate, no effect of time was found for normal gait (p = 0.164). For the backward gait, no significant effect of time was found (p = 0.072). However, post hoc tests showed a significant difference in the velocity of backward gait (p = 0.007) – similar to the force plate. For the tandem gait no effect of time was found (p = 0.077). However, in contrast to the force plate, the post-hoc tests revealed a significant difference in time for three out of four variables: For the stride time (p = 0.006), the velocity (p = 0.044) and the cadence (p = 0.002). No significant effect was found for the step width.

While the force plate analysis revealed an effect of time for the tandem stance, the sensor system analysis did not find a significant effect of time for any of the stance tasks (narrow stance, p = 0.213; tandem stance, p = 0.850; narrow stance with eyes closed, p = 0.203; single leg stance, p = 0.934).

### *4.2.3 Differences Over Time – Smartphone*

For the backward gait a significant effect of time was found (p = 0.021). Post hoc tests showed a significant difference in the velocity (p = 0.005), which is similar to both other gait analysis systems. In contrast to the other systems, no significant effect of time was found for the normal gait (p = 0.164) and similarly to the force plate analysis, no significant effect of time was found for the tandem gait (p = 0.378).

For both the narrow stance and the single leg stance, no effect of time was found (p = 0.145 and p = 0.107). However, in contrast to the other gait analysis systems, post hoc tests showed a significant difference in the speed of movement for the narrow stance (p = 0.047) and in the ellipse area for the single leg stance (p = 0.028). As in the sensor system, for neither the tandem stance nor the narrow stance with eyes closed there was a significant effect of time (p = 0.769 and p = 0.262, respectively).

### *4.2.4 Within-System Correlations*

Correlations are shown within one gait analysis system between the different variables of gait (Tab. 10, Tab. 11, Tab. 12) and stance (Tab. 13, Tab. 14, Tab. 15). Correlations were mostly moderate (0.4 to 0.69) to very strong (0.9 to 1), except for the step width.

**Gait – Force Plate**

| | | Normal gait T1 | | | | Backward gait T1 | | | | Tandem gait T1 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Cadence | Velocity | Step width [cm] | | Cadence | Velocity | Step width | | Cadence | Velocity | Step width |
| Stride time [s] | Cor. | **-0.980**$^{**}$ | **-0.746**$^{**}$ | 0.225 | | **-0.988**$^{**}$ | -0.372 | 0.384 | | **-0.968**$^{**}$ | **-0.792**$^{**}$ | -0.144 |
| | Sig. (2-tailed) | 0.000 | 0.000 | 0.280 | | 0.000 | 0.067 | 0.058 | | 0.000 | 0.000 | 0.544 |
| Cadence [steps/s] | Cor. | | **0.713**$^{**}$ | -0.304 | | | 0.374 | -0.394 | | | **0.869**$^{**}$ | 0.155 |
| | Sig. (2-tailed) | | 0.000 | 0.139 | | | 0.065 | 0.051 | | | 0.000 | 0.501 |
| Velocity [m/s] | Cor. | | | -0.096 | | | | -0.041 | | | | 0.183 |
| | Sig. (2-tailed) | | | 0.649 | | | | 0.845 | | | | 0.428 |
| | | N = 25 | | | | N = 25 | | | | N = 21 | | |

| | | Normal gait T2 | | | | Backward gait T2 | | | | Tandem gait T2 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Cadence | Velocity | Step width [cm] | | Cadence | Velocity | Step width | | Cadence | Velocity | Step width |
| Stride time [s] [s] | Cor. | **-0.993**$^{**}$ | **-0.814**$^{**}$ | 0.414 | | **-0.977**$^{**}$ | **-0.457**$^{*}$ | 0.422 | | **-0.916**$^{**}$ | **-0.860**$^{**}$ | -0.136 |
| | Sig. (2-tailed) | 0.000 | 0.000 | 0.069 | | 0.000 | 0.043 | 0.064 | | 0.000 | 0.000 | 0.578 |
| Cadence [steps/s] | Cor. | | **0.840**$^{**}$ | -0.427 | | | 0.414 | **-0.526**$^{*}$ | | | **0.941**$^{**}$ | 0.011 |
| | Sig. (2-tailed) | | 0.000 | 0.061 | | | 0.069 | 0.017 | | | 0.000 | 0.964 |
| Velocity [m/s] | Cor. | | | -0.413 | | | | -0.005 | | | | -0.249 |
| | Sig. (2-tailed) | | | 0.070 | | | | 0.984 | | | | 0.319 |
| | | N = 20 | | | | N = 20 | | | | N = 19 | | |
| *. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed). | | | | | | | | | | | | |

Tab. 10: Within-system correlations in the force plate analysis. Cor. = correlation after Pearson, T2 = second measurement point. Significant correlations are highlighted in bold

## Gait – Sensor System

Within the sensor system, moderate to very strong correlations existed between all variables, besides for the step width. This variable showed only two moderate but significant correlations within the tandem gait after the training interval (T2): One with stride time and one with velocity.

| | | Normal gait T1 | | | | Backward gait T1 | | | | Tandem gait T1 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Cadence** | **Velocity** | **Step width [cm]** | | **Cadence** | **Velocity** | **Step width** | | **Cadence** | **Velocity** | **Step width** |
| **Stride time [s]** | Cor. | **-0.985**** | **-0.861**** | 0.236 | | **-0.995**** | **-0.535**** | -0.199 | | **-0.950**** | **-0.740**** | -0.156 |
| | Sig. (2-tailed) | 0.000 | 0.000 | 0.267 | | 0.000 | 0.007 | 0.352 | | 0.000 | 0.000 | 0.488 |
| **Cadence [steps/s]** | Cor. | | **0.854**** | -0.280 | | | **0.521**** | 0.172 | | | **0.838**** | 0.153 |
| | Sig. (2-tailed) | | 0.000 | 0.184 | | | 0.009 | 0.422 | | | 0.000 | 0.497 |
| **Velocity [m/s]** | Cor. | | | -0.351 | | | | 0.134 | | | | 0.019 |
| | Sig. (2-tailed) | | | 0.093 | | | | 0.532 | | | | 0.932 |
| | | N = 24 | | | | N = 24 | | | | N = 24 | | |

| | | Normal gait T2 | | | | Backward gait T2 | | | | Tandem gait T2 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Cadence** | **Velocity** | **Step width [cm]** | | **Cadence** | **Velocity** | **Step width** | | **Cadence** | **Velocity** | **Step width** |
| **Stride time [s]** | Cor. | **-0.995**** | **-0.727**** | 0.273 | | **-0.993**** | **-0.472*** | -0.010 | | **-0.986**** | **-0.851**** | **-0.433*** |
| | Sig. (2-tailed) | 0.000 | 0.000 | 0.231 | | 0.000 | 0.031 | 0.967 | | 0.000 | 0.000 | 0.050 |
| **Cadence [steps/s]** | Cor. | | **0.727**** | -0.277 | | | **0.452*** | -0.027 | | | **0.759**** | 0.318 |
| | Sig. (2-tailed) | | 0.000 | 0.224 | | | 0.040 | 0.906 | | | 0.000 | 0.172 |
| **Velocity [m/s]** | Cor. | | | -0.113 | | | | 0.051 | | | | **0.580**** |
| | Sig. (2-tailed) | | | 0.625 | | | | 0.825 | | | | 0.007 |
| | | N = 21 | | | | N = 21 | | | | N = 21 | | |
| *. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed). | | | | | | | | | | | | |

Tab. 11: Within-system correlations in the sensor system. Cor. = correlation after Pearson, T1 = first study visit, T2 = second study visit

## Gait – Smartphone

For the smartphone app, moderate to very strong correlations exist between cadence and stride time for all three gait tasks, but not between velocity and the other two variables. Only one significant, moderate correlation was found for velocity, with stride time in the tandem gait at T2. Step width was not included in the analysis.

| | | **Normal gait T1** | | | **Backward gait T1** | | | **Tandem gait T1** | |
|---|---|---|---|---|---|---|---|---|---|
| | | **Cadence** | **Velocity [m/s]** | | **Cadence** | **Velocity** | | **Cadence** | **Velocity** |
| **Stride time [s]** | Cor. | **-0.985**$^{**}$ | 0.282 | | **-0.964**$^{**}$ | -0.058 | | **-0.969**$^{**}$ | -0.091 |
| | Sig. (2-tailed) | 0.000 | 0.273 | | 0.000 | 0.815 | | 0.000 | 0.711 |
| **Cadence [steps/s]** | Cor. | | -0.008 | | | 0.098 | | | 0.148 |
| | Sig. (2-tailed) | | 0.974 | | | 0.690 | | | 0.545 |
| | | N = 18 | | | N = 19 | | | N = 19 | |

| | | **Normal gait T2** | | | **Backward gait T2** | | | **Tandem gait T2** | |
|---|---|---|---|---|---|---|---|---|---|
| | | **Cadence** | **Velocity [m/s]** | | **Cadence** | **Velocity** | | **Cadence** | **Velocity** |
| **Stride time [s]** | Cor. | **-0.990**$^{**}$ | 0.040 | | **-0.987**$^{**}$ | 0.413 | | **-0.984**$^{**}$ | **-0.561**$^{*}$ |
| | Sig. (2-tailed) | 0.000 | 0.888 | | 0.000 | 0.207 | | 0.000 | 0.046 |
| **Cadence [steps/s]** | Cor. | | 0.069 | | | -0.441 | | | 0.530 |
| | Sig. (2-tailed) | | 0.808 | | | 0.175 | | | 0.062 |
| | | N = 15 | | | N = 11 | | | N = 13 | |
| *. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed). | | | | | | | | | |

Tab. 12: Within-system correlations in the smartphone analysis. Cor. = correlation after Pearson, T1 = first study visit, T2 = second study visit

Next, within-system correlations are shown for the balance variables, that is, the correlation between the sway area of the center of mass (COM) and the velocity of the COM at the same study visit and the same task. Within the force plate analysis and the sensor system nearly all correlations were moderate to strong and significant, while in the smartphone analysis correlations – if present – were weaker and only two of them reached significance: The tandem stance and the narrow stance with eyes closed at the second study visit (T2).

### Balance – Force Plate

| | | Narrow stance T1 | Tandem stance T1 | NS eyes closed T1 | Single leg stance T1 |
|---|---|---|---|---|---|
| | | COP velocity [mm/s] | COP velocity | COP velocity | COP velocity |
| COP ellipse [$mm^2$] | Cor. | **0.747**** | **0.562**** | **0.695**** | **0.520*** |
| | Sig. (2-tailed) | 0.000 | 0.004 | 0.000 | 0.019 |
| | | N = 25 | N = 24 | N = 24 | N = 20 |

| | | Narrow stance T2 | Tandem stance T2 | NS eyes closed T2 | Single leg stance T2 |
|---|---|---|---|---|---|
| | | COP velocity [mm/s] | COP velocity | COP velocity | COP velocity |
| COP ellipse [$mm^2$] | Cor. | **0.458*** | **0.855**** | **0.568**** | **0.759**** |
| | Sig. (2-tailed) | 0.042 | 0.000 | 0.005 | 0.000 |
| | | N = 20 | N = 20 | N = 20 | N = 20 |
| *. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed). | | | | | |

Tab. 13: Within-system correlations in the force plate analysis. Cor. = correlation after Pearson, T1 = first study visit, T2 = second study visit

### Balance – Sensor System

| | | Narrow stance T1 | Tandem stance T1 | NS eyes closed T1 | Single leg stance T1 |
|---|---|---|---|---|---|
| | | COP velocity [mm/s] | COP velocity | COP velocity | COP velocity |
| COP ellipse [$mm^2$] | Cor. | **0.834**** | 0.229 | **0.803**** | **0.863**** |
| | Sig. (2-tailed) | 0.000 | 0.306 | 0.000 | 0.000 |
| | | N = 24 | N = 22 | N = 23 | N = 20 |

| | | Narrow stance T2 | | Tandem stance T2 | | NS eyes closed T2 | | Single leg stance T2 |
|---|---|---|---|---|---|---|---|---|
| | COP velocity [mm/s] | | | COP velocity | | COP velocity | | COP velocity |
| COP ellipse [mm²] | Cor. | **0.655****** | | **0.749****** | | **0.800****** | | **0.851****** |
| | Sig. (2-tailed) | 0.002 | | 0.000 | | 0.000 | | 0.000 |
| | N = 20 | | | N = 20 | | N = 21 | | N = 18 |
| *. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed). | | | | | | | | |

Tab. 14: Within-system correlations in the sensor system. Cor. = correlation after Pearson, N = number of valid cases, T1 = first study visit, T2 = second study visit

## Balance – Smartphone

| | | Narrow stance T1 | | Tandem stance T1 | | NS eyes closed T1 | | Single leg stance T1 |
|---|---|---|---|---|---|---|---|---|
| | COP velocity [mm/s] | | | COP velocity | | COP velocity | | COP velocity |
| COP ellipse [mm²] | Cor. | 0.360 | | 0.007 | | 0.447 | | **0.732**** |
| | Sig. (2-tailed) | 0.156 | | 0.978 | | 0.109 | | 0.003 |
| N = 17 | | | | N = 16 | | N = 14 | | N = 14 |

| | | Narrow stance T2 | | Tandem stance T2 | | NS eyes closed T2 | | Single leg stance T2 |
|---|---|---|---|---|---|---|---|---|
| | COP velocity [mm/s] | | | COP velocity | | COP velocity | | COP velocity |
| COP ellipse [mm²] | Cor. | 0.482 | | 0.530 | | **0.620*** | | 0.388 |
| | Sig. (2-tailed) | 0.081 | | 0.093 | | 0.031 | | 0.268 |
| | N = 14 | | | N = 11 | | N = 12 | | N = 10 |
| *. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed). | | | | | | | | |

Tab. 15: Within-system correlations in the smartphone analysis. Cor. = correlation after Pearson, N = number of valid cases, T1 = first study visit, T2 = second study visit

## 4.3 Between-System Correlations

Correlations are shown between all gait analysis system for the different variables at T1. For normal gait, strong to very strong correlations existed between all variables, except for the step width, between the sensor system and the force plate. Negligible to moderate correlations existed between the smartphone app and the other two systems, five of them reaching statistical significance.

### Normal Gait

| | | | Sensor system | | | | | Smartphone | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | **Stride time** | **Velocity** | **Step width** | **Cadence** | | **Stride time** | **Cadence** | **Velocity** |
| **Force plate** | Stride time | Cor. | **0.981$^{**}$** | **-0.864$^{**}$** | 0.171 | **-0.963$^{**}$** | | 0.098 | -0.011 | **-0.550*** |
| | | Sig. (2-tailed) | 0.000 | 0.000 | 0.425 | 0.000 | | 0.710 | 0.967 | 0.018 |
| | Cadence | Cor. | **-0.983$^{**}$** | **0.864$^{**}$** | -0.246 | **0.992$^{**}$** | | -0.170 | 0.096 | **0.534*** |
| | | Sig. (2-tailed) | 0.000 | 0.000 | 0.247 | 0.000 | | 0.513 | 0.705 | 0.022 |
| | Velocity | Cor. | **-0.708$^{**}$** | **0.925$^{**}$** | -0.195 | **0.695$^{**}$** | | 0.004 | 0.146 | 0.417 |
| | | Sig. (2-tailed) | 0.000 | 0.000 | 0.360 | 0.000 | | 0.988 | 0.563 | 0.086 |
| | Step width | Cor. | 0.272 | -0.274 | **0.430$^{*}$** | -0.327 | | -0.211 | -0.125 | **-0.536*** |
| | | Sig. (2-tailed) | 0.199 | 0.195 | 0.036 | 0.119 | | 0.416 | 0.622 | 0.022 |
| | | | N = 24 | | | | | N = 18 | | |
| **Sensor system** | Stride time | Cor. | | | | | | 0.157 | -0.055 | *-0.476* |
| | | Sig. (2-tailed) | | | | | | 0.563 | 0.835 | *0.053* |
| | Cadence | Cor. | | | | | | -0.235 | 0.136 | **0.487*** |
| | | Sig. (2-tailed) | | | | | | 0.381 | 0.603 | 0.047 |
| | Velocity | Cor. | | | | | | -0.052 | 0.171 | **0.508*** |
| | | Sig. (2-tailed) | | | | | | 0.848 | 0,512 | 0.038 |
| | Step width | Cor. | | | | | | 0.393 | -0.452 | 0.171 |
| | | Sig. (2-tailed) | | | | | | 0.132 | 0.068 | 0.511 |
| | | | | | | | | N = 17 | | |
| *. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed). | | | | | | | | | | |

Tab. 16: Between-system correlations for normal gait (T1). Cor. = correlation after Pearson. Italic font indicates a significance by trend. N = number of valid cases

### Backward Gait

In the backward gait, similar but weaker patterns as in the normal gait were observed between the force plate and the sensor system. Between the smartphone and the other two gait analysis systems, only one correlation reached statistical significance (velocity of JTrack with velocity of the force plate).

| | | | Sensor system | | | | | Smartphone | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Stride time | Velocity | Step width | Cadence | | Stride time | Cadence | Velocity |
| Force plate | Stride time | Cor. | **0.731**$^{**}$ | **-0.475**$^{*}$ | -0.340 | **-0.699**$^{**}$ | | 0.270 | -0.276 | -0.103 |
| | | Sig. (2-tailed) | 0.000 | 0.019 | 0.104 | 0.000 | | 0.264 | 0.252 | 0.674 |
| | Cadence | Cor. | **-0.714**$^{**}$ | **0.408**$^{*}$ | 0.356 | **0.687**$^{**}$ | | -0.297 | 0.301 | 0.176 |
| | | Sig. (2-tailed) | 0.000 | 0.048 | 0.088 | 0.000 | | 0.217 | 0.211 | 0.471 |
| | Velocity | Cor. | -0.150 | **0.453**$^{*}$ | 0.110 | 0.138 | | -0.183 | 0.244 | **0.588**$^{**}$ |
| | | Sig. (2-tailed) | 0.485 | 0.026 | 0.610 | 0.520 | | 0.453 | 0.315 | 0.008 |
| | Step width | Cor. | 0.353 | -0.107 | -0.195 | -0.379 | | 0.062 | -0.047 | -0.020 |
| | | Sig. (2-tailed) | 0.090 | 0.619 | 0.361 | 0.068 | | 0.800 | 0.847 | 0.936 |
| | | | N = 24 | | | | | N = 19 | | |
| Sensor system | Stride time | Cor. | | | | | | 0.165 | -0.209 | 0.114 |
| | | Sig. (2-tailed) | | | | | | 0.513 | 0.404 | 0.652 |
| | Cadence | Cor. | | | | | | -0.178 | 0.219 | -0.112 |
| | | Sig. (2-tailed) | | | | | | 0.479 | 0.382 | 0.659 |
| | Velocity | Cor. | | | | | | -0.109 | 0.152 | 0.087 |
| | | Sig. (2-tailed) | | | | | | 0.667 | 0.548 | 0.733 |
| | Step width | Cor. | | | | | | 0.031 | -0.076 | 0.301 |
| | | Sig. (2-tailed) | | | | | | 0.904 | 0.766 | 0.224 |
| | | | | | | | | N = 18 | | |
| *. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed). | | | | | | | | | | |

Tab. 17: Between-system correlations for the backward gait at T1. Cor. = correlation after Pearson, N = number of valid cases

## Tandem Gait

In the tandem gait, similar patterns as in the two other gait tasks were again observed between the sensor system and the force plate. Between the smartphone and the sensor system, patterns were similar to the ones in the backward gait. Between the smartphone and the other two systems, four correlations reached statistical significance (two with smartphone velocity and two with step width of the sensor system).

| | | | Sensor system | | | | Smartphone | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | **Stride time** | **Velocity** | **Step width** | **Cadence** | **Stride time** | **Cadence** | **Velocity** |
| **Force plate** | Stride time | Cor. | **0.901$^{**}$** | **-0.535$^{*}$** | -0.310 | **-0.836$^{**}$** | -0.217 | 0.228 | -0.155 |
| | | Sig. (2-tailed) | 0.000 | 0.018 | 0.226 | 0.000 | 0.436 | 0.413 | 0.580 |
| | Cadence | Cor. | **-0.862$^{**}$** | **0.581$^{**}$** | 0.193 | **0.861$^{**}$** | 0.138 | -0.143 | 0.151 |
| | | Sig. (2-tailed) | 0.000 | 0.007 | 0.442 | 0.000 | 0.623 | 0.611 | 0.591 |
| | Velocity | Cor. | **-0.696$^{**}$** | **0.618$^{**}$** | 0.193 | **0.699$^{**}$** | -0.239 | 0.234 | **0.515*** |
| | | Sig. (2-tailed) | 0.001 | 0.004 | 0.442 | 0.001 | 0.392 | 0.401 | 0.050 |
| | Step width | Cor. | -0.154 | 0.278 | -0.403 | 0.165 | -0.268 | 0.240 | 0.005 |
| | | Sig. (2-tailed) | 0.516 | 0.234 | 0.097 | 0.486 | 0.334 | 0.389 | 0.987 |
| | | | N = 19 | | | | N = 15 | | |
| **Sensor system** | Stride time | Cor. | | | | | -0.268 | 0.329 | -0.224 |
| | | Sig. (2-tailed) | | | | | 0.281 | 0.183 | 0.371 |
| | Cadence | Cor. | | | | | 0.216 | -0.264 | 0.270 |
| | | Sig. (2-tailed) | | | | | 0.389 | 0.290 | 0.279 |
| | Velocity | Cor. | | | | | -0.076 | 0.024 | **0.534*** |
| | | Sig. (2-tailed) | | | | | 0.763 | 0.926 | 0.022 |
| | Step width | Cor. | | | | | **0.519*** | **-0.577*** | -0.002 |
| | | Sig. (2-tailed) | | | | | 0.033 | 0.015 | 0.994 |
| | | | | | | | N = 17 | | |
| *. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed). | | | | | | | | | |

Tab. 18: Between-system correlations for the tandem gait at T1. Cor. = correlation after Pearson, N = number of valid cases

### Stance Tasks

Correlations between the systems in the stance tasks are shown for T1. Rows and columns without a significant correlation were removed from the table to improve readability and facilitate an overview. Similar to the correlations for gait, several positive significant correlations were found between the sensor system and the force plate, while only two positive significant correlations were found between smartphone and force plate, and no positive significant correlation between smartphone and sensor system. No significant correlations with smartphone variables were found for normal stance.

| | | | Sensor system | | | | | | | | Smartphone | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | NS velocity | NS ellipse | TS velocity | TS ellipse | NSEc velocity | NSEc ellipse | SS velocity | SS ellipse | TS ellipse | TS velocity | NSEc ellipse | NSEc velocity | SS ellipse | SS velocity |
| Force plate | NS ellipse | Cor. | **,655$^{**}$** | **,697$^{**}$** | 0,170 | 0,066 | 0,376 | 0,340 | -0,005 | -0,211 | **,531$^{*}$** | -0,142 | 0,220 | 0,078 | -0,085 | 0,112 |
| | | Sig. | 0,001 | 0,000 | 0,450 | 0,766 | 0,070 | 0,112 | 0,982 | 0,372 | 0,034 | 0,586 | 0,450 | 0,775 | 0,773 | 0,680 |
| | | *N* | *24* | *24* | *22* | *23* | *24* | *23* | *21* | *20* | *16* | *17* | *14* | *16* | *14* | *16* |
| | NS velocity | Cor. | **,673$^{**}$** | **,534$^{**}$** | 0,238 | -0,047 | **,412$^{*}$** | 0,335 | 0,264 | -0,037 | **,588$^{*}$** | -0,378 | 0,047 | 0,007 | -0,090 | -0,095 |
| | | Sig. | 0,000 | 0,007 | 0,286 | 0,831 | 0,046 | 0,118 | 0,247 | 0,875 | 0,017 | 0,134 | 0,874 | 0,979 | 0,760 | 0,728 |
| | | *N* | *24* | *24* | *22* | *23* | *24* | *23* | *21* | *20* | *16* | *17* | *14* | *16* | *14* | *16* |
| | TS ellipse | Cor. | 0,048 | 0,294 | 0,371 | **,483$^{*}$** | 0,221 | 0,096 | -0,095 | -0,074 | -0,105 | 0,305 | -0,154 | -0,270 | **-,564$^{*}$** | -0,382 |
| | | Sig. | 0,825 | 0,164 | 0,090 | 0,020 | 0,300 | 0,664 | 0,683 | 0,757 | 0,698 | 0,234 | 0,599 | 0,311 | 0,036 | 0,144 |
| | | *N* | *24* | *24* | *22* | *23* | *24* | *23* | *21* | *20* | *16* | *17* | *14* | *16* | *14* | *16* |
| | TS velocity | Cor. | 0,326 | 0,335 | **,468$^{*}$** | 0,292 | 0,322 | 0,176 | 0,289 | 0,189 | -0,310 | -0,009 | **-,607$^{*}$** | -0,238 | -0,331 | -0,155 |
| | | Sig. | 0,129 | 0,119 | 0,028 | 0,177 | 0,135 | 0,432 | 0,204 | 0,424 | 0,261 | 0,973 | 0,028 | 0,392 | 0,270 | 0,581 |
| | | *N* | *23* | *23* | *22* | *23* | *23* | *22* | *21* | *20* | *15* | *16* | *13* | *15* | *13* | *15* |
| | NSEc ellipse | Cor. | **,474$^{*}$** | **,680$^{**}$** | 0,030 | 0,252 | **,715$^{**}$** | **,782$^{**}$** | 0,086 | -0,067 | -0,111 | -0,224 | -0,215 | -0,145 | -0,368 | 0,040 |
| | | Sig. | 0,022 | 0,000 | 0,893 | 0,258 | 0,000 | 0,000 | 0,720 | 0,785 | 0,683 | 0,387 | 0,461 | 0,592 | 0,195 | 0,882 |
| | | *N* | *23* | *23* | *22* | *22* | *23* | *23* | *20* | *19* | *16* | *17* | *14* | *16* | *14* | *16* |
| | NSEc velocity | Cor. | **,534$^{**}$** | **,483$^{*}$** | 0,121 | 0,299 | **,752$^{**}$** | **,605$^{**}$** | 0,091 | -0,126 | 0,194 | -0,091 | -0,014 | -0,012 | -0,164 | 0,063 |
| | | Sig. | 0,007 | 0,017 | 0,592 | 0,165 | 0,000 | 0,002 | 0,696 | 0,598 | 0,472 | 0,727 | 0,963 | 0,964 | 0,576 | 0,815 |
| | | *N* | *24* | *24* | *22* | *23* | *24* | *23* | *21* | *20* | *16* | *17* | *14* | *16* | *14* | *16* |

| | | | Sensor system | | | | | | | | Smartphone | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | NS velocity | NS ellipse | TS velocity | TS ellipse | NSEc velocity | NSEc ellipse | SS velocity | SS ellipse | TS ellipse | TS velocity | NSEc ellipse | NSEc velocity | SS ellipse | SS velocity |
| | SS ellipse | Cor. | 0,349 | 0,291 | 0,285 | 0,188 | 0,323 | 0,089 | ,660** | ,672** | 0,238 | -,601* | -0,306 | -0,346 | -0,135 | 0,293 |
| | | Sig. | 0,143 | 0,227 | 0,252 | 0,442 | 0,178 | 0,725 | 0,002 | 0,002 | 0,456 | 0,030 | 0,333 | 0,246 | 0,693 | 0,331 |
| | | N | 19 | 19 | 18 | 19 | 19 | 18 | 19 | 18 | 12 | 13 | 12 | 13 | 11 | 13 |
| | SS velocity | Cor. | 0,189 | 0,279 | 0,168 | -0,088 | 0,000 | 0,107 | ,706** | ,679** | -0,203 | -0,240 | -0,444 | -0,475 | -,624* | -,626* |
| | | Sig. | 0,388 | 0,197 | 0,455 | 0,689 | 1,000 | 0,635 | 0,000 | 0,001 | 0,467 | 0,372 | 0,129 | 0,073 | 0,023 | 0,012 |
| | | N | 23 | 23 | 22 | 23 | 23 | 22 | 21 | 20 | 15 | 16 | 13 | 15 | 13 | 15 |
| | | | | | | | | | | | | | | | | |
| Sensor system | NS velocity | Cor. | | | | | | | | | 0,500 | -,621* | 0,012 | 0,255 | 0,053 | 0,140 |
| | | Sig. | | | | | | | | | 0,058 | 0,010 | 0,969 | 0,359 | 0,864 | 0,620 |
| | | N | | | | | | | | | 15 | 16 | 13 | 15 | 13 | 15 |
| | SS velocity | Cor. | | | | | | | | | -0,260 | -0,512 | -0,451 | -,576* | -,656* | 0,116 |
| | | Sig. | | | | | | | | | 0,392 | 0,061 | 0,164 | 0,040 | 0,029 | 0,705 |
| | | N | | | | | | | | | 13 | 14 | 11 | 13 | 11 | 13 |
| | SS ellipse | Cor. | | | | | | | | | -0,290 | 0,148 | -0,380 | -,685* | -,689* | -0,527 |
| | | Sig. | | | | | | | | | 0,361 | 0,630 | 0,279 | 0,014 | 0,019 | 0,078 |
| | | N | | | | | | | | | 12 | 13 | 10 | 12 | 11 | 12 |

*. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed).

Tab. 19: Between-system correlations for the stance tasks at T1. Cor. = correlation after Pearson, N = number of valid cases, NS = narrow stance, TS = tandem stance, NSEc = narrow stance with eyes closed, SS = single leg stance

# 5 Discussion

This study investigated several gait and balance tasks in healthy adults before and after a three-week gait and balance training, and compared the smartphone with two other gait analysis systems for the evaluation of these tasks.

Since physical activity is known to have a significant impact on mental well-being and vice versa, the motor assessment in this study was accompanied by several questionnaire scores addressing depression, anxiety, general well-being, stress, self-efficacy, optimism, pessimism and balance confidence. However, although most of the questionnaires were supposed to address different aspects of mental well-being or abilities, they were clearly related to each other with moderate to even strong correlations: For example, a higher depression score correlated moderately with a higher stress score and strongly with a lower general habitual well-being, or a higher anxiety score correlated moderately with a higher depression score, with a lower self-efficacy and with a lower general habitual well-being. Only weak but non-significant correlations were found for the pessimism part of the SWOP-K9 questionnaire and only one moderate correlation was found for the ABC-D score with the stress score of the PHQ questionnaire. However, compared to the other questionnaires used, the ABC-D questionnaire focused less on emotional aspects or attitudes and more on the individual assessment of physical abilities, so that lack of correlations was not surprising.

## 5.1 Differences Over Time – Training Effects

### *5.1.1 Questionnaires*

The questionnaire scores did not differ significantly between the two study visits T1 and T2. This indicates that the here performed gait and balance training did not have an impact on self-efficacy, optimism, pessimism, general habitual well-being or on activity-specific balance confidence. This is an unexpected result, as physical exercise and movement is known to improve mood and self-efficacy (White et al., 2009). Physical therapy or exercises can reduce fatigue and improve the capability to improve one's emotional life (Fischetti et al., 2019) and Mikkelsen et al. (2017) cited several positive effects of physical activity on mental health in their review and even write that it can improve mental well-being as well as psychotherapy. On the other hand, female participants had a mean score of 56.7 (±15.9) points in the FAHW questionnaire at T1 and male participants had a mean score of 61.8 (±18.1) points, which is above-average for female and even strongly above-average for male participants (according to reference values for healthy men and women in Wydra, 2014). This indicates that the general well-being of the participants was already at a high level before the intervention and hence does not leave much room for improvement.

Due to several constraints (study duration, compliance), a three-week period was chosen as the training period in this study. While Mikkelsen et al. (2017) reported that exercising for 15 minutes three times per week already reduced depressive symptoms, most studies have chosen a longer time period for the training program or a longer duration for each unit. For instance, a large cross-sectional study in the USA showed the strongest effects of physical exercise on mental health with a training duration of 45 minutes or at frequencies of three to five times per week (Chekroud et al., 2018). Sherrington et al. (2008) even recommended a minimum of two hours per week for 25 weeks to maximize the effectiveness of balance training and to prevent falls. In a more specific context, the highest effectiveness of video-based rehabilitation programs was found after at least of four weeks (Kim et al., 2016). Thus, on the one hand, a higher training volume or frequency can lead to better training results.

On the other hand, a higher training volume could also reduce compliance, as the subjective cost may exceed the subjective benefit of the training. In Haines et al. (2009), a drop in compliance was found already after three weeks. During our study, lasting four weeks, we did not observe any apparent decrease in compliance (as measured by the number of training sessions and home measurements taken). We tried to reach a high compliance by trying to avoid reasons to lose compliance and trying to implement possibilities to increase compliance named in the study from Essery et al. (2017). For example, the JuTrack EMA App, which we used for answering questionnaires once a week, serves as an automatic reminder for the participants to complete their questionnaires and exercises. In the gait and balance training via offline video footage, exercises were explained in detail and the purpose of the exercise was tried to be made understandable. It was allowed to recruit friends or relatives for the study.

Regardless of training volume, frequency and compliance, the content of the training plays an important role for its success. As indicated by the oral or written feedback from some participants, the demands were perceived differently, ranging from “very demanding and challenging” to “not challenging enough”. This is not unexpected, as the age range of the participants was quite large and motor skills or athleticism vary across random samples and different age groups. Therefore, training should probably be more individualized in the future, or more specific groups (e.g. smaller age range or more homogenous with respect to motor skills) should be preferred. It should be noted that feedback was given in a free form rather than in a standardized manner. This could be improved in the future to better evaluate the feedback.

Nevertheless, small changes in the minimum and maximum scores can be observed (e.g. higher minimum self-efficacy score, higher maximum well-being score) and indicate that larger changes could possibly occur with a more intense or longer training program. However, the volume of training is still much lower compared to the time spent in other daily activities (e.g. work), so it is not only gait and balance training that affects the questionnaire scores. Therefore, the scores may not be sensitive enough to detect training-induced changes. Additionally, as indicated earlier, general well-being of the participants already was at a high level before the intervention.

### *5.1.2 Gait Performance*

Mean values of gait variables were comparable to those found in the literature, e.g. our values for stride time (0.94s-1.2s in normal gait at T1) were similar to a healthy control group in Pawik et al. (2021), with a stride time of 1.16s, and to the mean value of male and female police officers without carrying police equipment (averaged stride time of 1.09s, Kasović et al., 2020). Similarly, cadence (1.7 and 1.7 steps/s), velocity (0.98 and 0.97m/s) and step width (11.64cm and 10.6cm) of both force plate and sensor system, respectively, were a bit lower but comparable to the values of the police officers (1.83 steps/s, 1.25m/s and 11.65cm). The smartphone app values were consistent with the other two systems for stride time and cadence (1.22s and 1.6 steps/s), while the value for velocity was around two-thirds lower (0.32m/s) and thus not consistent with the literature. For the backward gait, a control group of healthy adults (mean age 37.2y) showed a stride time of 1.2s, a cadence of 1.68 steps/s, a velocity of 0.87m/s and step width of 16.8cm (Gimunová et al., 2021). These values were close to our results from all three applied gait analysis systems (stride time: 1.22/1.21/1.23s, cadence: 1.66/1.66/1.65 steps/s, velocity: 0.69/0.66/0.3m/s, step width: 18.08/11.86cm). Compared to the literature, the velocity values differed the most and were around 20% lower for the force plate and sensor system and even about 65% lower for the smartphone. For step width, the sensor system values were lower compared to the literature, which is probably related to the calibration of the system: The closer the participants' feet were in the "neutral position", the smaller the absolute values of the step width were in the later analysis. Another study described a mean velocity of 0.98m/s for a control group of 14 healthy adults (mean age 44y) (Edwards et al., 2020), which is slightly faster than in our study sample. For the tandem gait, most studies reported only mean times (e.g. Oldham et al., 2017, Santo et al., 2021) or presented the results as a graph: A comparable sample of healthy adults (mean age 46.3y) showed cadence values of approximately 0.8 steps/s (Kronenbuerger et al., 2009), which is lower than the values found here (1.23, 1.19 and 1.57 steps/s, respectively). One study was found in which healthy older adults (mean age 84y) showed a cadence of 0.88 steps/s, a velocity of 0.27m/s and a step width of 3.5cm in the tandem gait (Rao et al., 2011), which is a bit lower compared to our values (1.23/1.19/1.57 steps/s, 0.45/0.4/0.23m/s, 2.24/2.44cm – for the force plate, sensor system and smartphone, respectively), probably due to age. Only the step width is comparable between the two studies. It should also be noted that in the tandem gait the heel of one foot is normally placed directly in front of the toes of the other foot. In our study, however, a hand's width of space had to be left between the feet to allow the force plate to distinguish between left and right foot. This may have facilitated the task and resulted in better gait performance.

Mean values of stride time and cadence were quite similar for all three gait analysis systems, while the mean values of velocity were considerably lower in the smartphone app. For example, normal gait had mean values of 0.98m/s and 0.97m/s in the force plate and sensor system, respectively, but a mean value of 0.32m/s in the smartphone app. In general, a high similarity for the mean values was expected between the JTrack data and the data of the other two systems. This was proven true for stride time and cadence, where mean values were quite similar, while the differences in the velocity were unexpectedly large. Various reasons could have played a role in this. For example, there are differences between the JTrack app and the force plate when recording the data, since the latter registers the foot print directly at the force plate and can thus easily determine the respective variables from the position data. This is less direct for both the JTrack app and the sensor system, as they use accelerometers and thus only indirect position data (derivate of the acceleration data). For the same reason, gravitational influences must also be filtered out, as they can distort the data. In addition, the sensor system uses multiple sensors, e.g. directly on the feet, while the JTrack app has only one sensor near the COM. This enables the sensor system to determine the relative positions of the sensors to one another. Taking these methodological-related differences into account, the differences were still larger than expected.

There were significant improvements for some of the variables between T1 and T2. For the force plate, stride time decreased, cadence increased (more steps per time), velocity increased and step width decreased for the normal gait; stride time decreased and velocity increased in the backward gait. In the sensor system, stride time decreased and cadence increased in the normal gait, velocity increased in the backward gait and stride time decreased, cadence increased and velocity increased in the tandem gait. For the smartphone, velocity increased in the backward gait. These are expected and desirable changes in terms of improved gait performance after a training intervention, although comparable studies in healthy adults are currently lacking. Nevertheless, in a patient study by Conradsson et al. (2015), PD patients participated in a 10-week balance training program for three times per week and 60 minutes per session. They showed increased velocity and step length after training. In another study with PD patients, improvements in velocity, stride length and cadence were observed after therapist-supervised training (Atterbury & Welman, 2017). The results, mentioned for normal gait in the force plate, replicated only for stride time and cadence in the sensor system and not at all in the smartphone app. However, the mean values show tendencies in the same direction, even if statistical significance was not reached. Only the velocity of the normal gait in the smartphone app showed almost the same value at T1 and T2. Similar patterns of improvement can be seen for backward gait and tandem gait for all three systems as well, but in the force plate only stride time and velocity in the backward gait reached a significance by trend ($p<0.06$). In the sensor system, velocity in the backward gait reached a significance by trend and stride time, cadence and velocity improved significantly in the tandem gait. Contrary to the overall (although not always significant) improvement, step width in the tandem gait was the only variable that did not show an improvement (mean value 2.4cm at T1 and 2.8cm at T2) in the sensor system. In the smartphone app, velocity improved significantly in the backward gait.

Altogether, a general improvement in gait variables was observed across all gait analysis systems, even though this could not be confirmed for all variables from a statistical point of view. These statistical differences depend on two other factors. First, the number of valid values that could be included in the statistical analysis was lower for the smartphone data, reducing the statistical power of the analysis, and second, the values obtained with the smartphone had higher standard deviations, both of which affects the outcome of the MANOVA. In addition, recent studies have identified gait variability, as measured by the standard deviation, as one of the most discriminatory variables between individuals with ataxia and healthy controls (Shah et al., 2021). Gait variability was not selected as a variable for analysis, because it was not available for all systems, but should be considered in future if possible.

In summary, all three gait analysis systems showed a comparable improvement in gait parameters, although in the best case all systems would have shown significance in the exact same variables over time. The observed improvement between T1 and T2 is probably caused by the training performed in between. However, a control group undergoing the measurements at T1 and T2 without any training in the meantime is missing and therefore a learning effect cannot be entirely excluded. To confirm and substantiate the positive effects of this study, further investigation, including a control group, seems reasonable.

### *5.1.3 Balance Performance*

Remarkably, the absolute values of both ellipse area and velocity differed quite strongly among the three gait analysis systems, especially for the ellipse area (narrow stance: 720/1522/1482mm$^2$, tandem stance: 1430/1515/2513mm$^2$, narrow stance with eyes closed: 981/1731/1467mm$^2$, single leg stance: 878/3860/1842mm$^2$), but for velocity as well (narrow stance: 15.6/6.6/16.3mm/s, tandem stance: 52.3/8.6/17.0mm/s, narrow stance with eyes closed: 27.6/8.7/16.9mm/s, single leg stance: 53.6/13.1/16.9mm/s). Nevertheless, moderate to strong correlations exist between the force plate and the sensor system (see section 4.3 Between-System Correlations). According to the mean values of these two variables, the tandem stance and the single leg stance appear to be the most challenging of the four stance tasks. However, no clear pattern was visible when displaying the mean values for all systems and both study visits (see Fig. 7).

Mean values of the balance performance are comparable with the literature. A control group of 44 healthy young adults (mean age 23.1y) showed an average ellipse area of 44.1mm$^2$ at normal stance in Nusseck and Spahn (2020) and healthy adults between 21 to 69 years showed an average ellipse area of 70±44mm$^2$ and a velocity of 24.3±10.8mm/s at normal stance in Pomarino et al. (2013). In our study, the velocity is comparable or slightly higher than the values for the narrow stance: We found mean velocities of 15.6, 6.6 and 16.3mm/s (for force plate, sensor system and smartphone, respectively). However, the values for the area of ellipse are very different from those in our study: Here we found mean values of 719.9, 1521.9 and 1746.1mm$^2$, respectively. At first glance, this is very surprising, but it certainly depends on methodological differences regarding the calculation, which is not specified in the studies mentioned. Pomarino et al. (2013) mention though, that their balance measures were averaged over the recording time. This could mean that $mm^2$ values are given as mean per second. As stance tasks in our study were recorded for 30s, the average values for normal stance are 24, 50.7 and $58.2mm^2$, respectively, which again is comparable to or slightly lower than in the studies by Nusseck and Spahn (2020) and Pomarino et al. (2013). For the other stance tasks, there were few reference values for healthy adults. One study reported an ellipse area of $138mm^2$ for the single leg stance in a control group of older adults (mean age 65.4y, W. Sun et al., 2018), while we found values of 878, 3860 and $1842mm^2$ in our study (averaged values per second: 29, 129 and $61.4mm^2$). However, it is unclear if the values were averaged in the cited study. If so, the values in our study were somewhat lower compared to the literature, possibly due to a lower mean age of the participants. The velocities were only reported separately for mediolateral and anteroposterior directions and are thus not comparable to our values. Terra et al. (2020) examined the same stance tasks in PD patients that we chose for our study and found the lowest values for the COM ellipse and narrow stance velocity, followed by narrow stance with eyes closed, then tandem stance and finally single leg stance. Because the three gait analysis systems in our study produced different results (see Fig. 7), this order could only partially be replicated: The same order could only be found for the sensor system at both study visits, while the other two systems showed higher values for the tandem stance than for the single leg stance and the smartphone showed similar values for the narrow stance and narrow stance with eyes closed at T1.

Statistical analysis did not show many significant improvements in balance performance from study visit T1 to study visit T2 after training. A significant difference was found in the force plate, where the mean velocity decreased in the tandem stance. The second and third significant differences were found in the smartphone app, which showed a significant decrease in movement speed for narrow stance and a significant decrease in the ellipse area for single leg stance. The sensor system did not show any significant differences. In contrast to the gait tasks, where small improvements in performance were observed for all variables (even though not always reaching statistical significance), there were some variables in the balance tasks that showed no tendencies of improvement (see Tab. 9): For example, the area of the ellipse increased in the single leg stance in the force plate, and it increased for all stance tasks except the single leg stance in the smartphone app. Velocities increased slightly but unexpectedly in the narrow stance (force plate), tandem stance (sensor system and smartphone) and single leg stance (smartphone). While comparable studies with healthy adults are missing, some patient studies reported clearer patterns of improvement. In other studies, clearer patterns of improvement could be observed. For example, Stożek et al. (2016) compared PD patients with and without a rehabilitation program in several gait and balance tasks, and found significant improvements for all parameters directly after and one month after the training program. However, this cannot be generalized to healthy adults, as the baseline performance is expected to be worse for PD patients. Cadore et al. (2013) also summarized in their review, that most balance trainings led to enhancements in balance. Again, the results cannot necessarily be compared with ours, as the studies examined there investigated effects in older adults with physical frailty and not in healthy adults.

### *5.1.4 Summary*

While improvements were found for both gait and balance performance, this effect was more pronounced for gait performance. Agreement between the three gait analysis systems was found only partially, again with a higher agreement for the gait variables. For the future, the most effective intervention program would combine a longer time frame for exercise interventions with major efforts to maintain or even improve study compliance. For this purpose, some simple steps could be added in future to increase compliance – for example, the smartphone app could include some sort of “to do list”, so that it is obvious to participants what steps they have completed already and how much of their tasks remain.

## 5.2 Evaluation of Gait Analysis Systems

First of all, it should be noted that the number of valid cases was lower for all variables within the T2 measurement point than within the T1 measurement point. This has an impact on the statistical significance of a correlation. However, differences are moderate for the force plate and sensor system (e.g. 25 vs. 20 participants, 24 vs. 21 participants), but more pronounced for the smartphone app (e.g. 19 vs. 11 participants in the backward gait).

Within the force plate analysis, there were several significant correlations between gait variables and between balance variables. The pattern of correlation between normal gait and tandem gait was similar, showing correlations between all time-related variables, while no correlations were found for step width. More precisely, stride time correlated negatively and very strongly with the cadence (less stride time, more steps per second). Velocity correlated strongly with stride time and cadence in normal gait and tandem gait, for both T1 and T2. In contrast, in the backward gait velocity correlated only weakly to moderately with stride time and cadence at both T1 and T2, and only the correlation between velocity and stride time at T2 reached statistical significance. A very strong correlation was found between cadence and stride time and negligible to moderate correlations were found for the step width with the other variables, similar to normal and tandem gait. One moderate, negative correlation between step width and cadence in the backward gait at T2 (more cadence, less step width) was the only correlation where the step width reached statistical significance. Altogether, after the training interval most correlations got slightly stronger and for backward gait even two further correlations gained significance. Most interestingly, this included also one correlation with step width. Moderate to strong positive correlations were also found between the balance variables (COM ellipse area and velocity) for all stance tasks. This is an expected result, as participants who are more unstable tend to have both a larger ellipse area and a higher movement velocity (e.g. younger kids, Pomarino et al., 2013). However, the pattern of correlation changed after the training interval: While before the training interval the strongest correlation was found for narrow stance (r=0.747) and the weakest correlation for the single leg stance (r=0.520), this was the other way around after the training interval (r=0.458 and r=0.759, respectively). Moreover, the strongest correlation after the training interval was found for the two variables of tandem stance (r=0.855).

In the Xsens software, similar correlations as in the force plate were found between stride time and cadence in all three gait tasks. The pattern of moderate to very strong correlations between the time-related variables was very similar to the pattern observed with the force plate system at T1 for normal gait and tandem gait. In contrast to the force plate system, correlations with velocity reached statistical significance in the backward gait as well, for both T1 and T2 (more velocity, less stride time and higher cadence), while again no correlations were found for step width. After the training interval, however, two moderate correlations with step width (and stride time/velocity) reached significance in the tandem gait (less step width with more stride time and less velocity). Again, step width in summary showed mostly negligible to weak correlations to the other variables. Besides the two newly added correlations with step width, the correlation coefficients remained stable or even decreased a bit from T1 to T2, which is in contrast to the increased correlation coefficients in the force plate system. For the balance variables, similar patterns as in the force plate analysis were found, except for the tandem stance at T1, where only a weak positive correlation was observed. In contrast to the force plate, the single leg stance consistently showed the highest correlation at both T1 and T2.

For the smartphone data, similar correlations to the other two systems were again found between stride time and cadence for all three gait tasks. However, velocity showed negligible to moderate correlations with stride time and cadence and only one correlation in the tandem gait reached statistical significance (less velocity with more stride time at T2). Surprisingly, the balance variables overall only showed moderate correlations and only two of them reached statistical significance: the single leg stance and T1 (r=0.732) and the narrow stance with eyes closed at T2 (r=0.620). However, the other variables showed moderate correlations as well. Only one negligible correlation was found between the COM ellipse area and velocity in the tandem stance at T1, similarly to the sensor system analysis, where also only a weak correlation was found for these variables. As mentioned earlier, fewer valid cases were available for the smartphone analysis, which affects the statistical analysis. No one-sided change in the correlation pattern could be observed before and after the training intervention, but three out of four correlation coefficients increased, while only one (single leg stance) decreased. The two strongest changes occurred firstly in the tandem stance, where a negligible correlation was found at T1 (r=0.007), but a moderate correlation at T2 (r=0.530), although both not reaching statistical significance; and secondly in the single leg stance, where a strong, significant correlation was found at T1 (r=0.732) and only a weak correlation at T2 (r=0.388).

In summary, moderate to very strong correlations were found between most of the variables within a system, except for the step width, which correlated only moderately or not at all with any of the other variables within a system. The consistency of the observed correlations between most gait variables – independently of the applied system and training – indicates a basic and quite stable relationship between these parameters. Only minor differences were observed between T1 and T2, again indicating a stable relationship within the variables of one system. Compared to the other systems, the smartphone provided the lowest correlation coefficients. As a consequence, an improvement in data accuracy should be attempted by reducing interference factors and by improving the evaluation of outcome variables.

### *5.2.1 Conformance of the Three Gait Analysis Systems*

When putting the three systems in relation to each other, moderate to very strong correlations were found between most of the gait variables of the force plate and the sensor system, except for step width. In detail, strong to very strong correlations (r>0.83) were found between stride time and cadence in normal gait and tandem gait, while they were slightly weaker in the backward gait (r>0.68). Velocity correlated strongly with cadence and stride time in normal gait (r>0.7), moderately in tandem gait (r>0.54), but only weakly to moderately in backward gait (ranging from r=0.11 to r=0.475). In the case of step width, only one correlation reached statistical significance: The correlation between the two step width values in normal gait of both systems (r=0.43). All named correlations were in accordance with the expected direction, i.e. significant correlations between cadence and velocity were positive (higher cadence, higher velocity) and correlations between stride time and the other two variables were negative (less stride time, higher cadence and higher velocity). Next, outcomes of the smartphone were compared to the other two analysis systems. For normal gait, only the smartphone velocity showed moderate correlations with any of the variables of the force plate: A higher velocity was related to less stride time and step width, and to a higher cadence. For backward gait and tandem gait, only the correlation between the two velocity values of force plate and the smartphone showed a significant, moderate correlation. Between smartphone and the sensor system, two correlations were significantly, moderately correlated in normal gait: A higher velocity in the smartphone data was related to a higher cadence and velocity in the sensor system. No significant correlation between any of the variables was found in backward gait. In the tandem gait, the two velocity values again showed a significant, moderate correlation, similar to the smartphone compared to the force plate. Additionally, lower step width in the sensor system was related to lower stride time and higher cadence in the smartphone.

Interestingly, the gait analysis systems show the best agreement within the normal gait, followed by tandem gait and a clearly lower agreement with backward gait. Comparable to the results of Steins et al. (2014), who have found only moderate agreement between an iPod touch and the sensor system, we found moderate correlations at the most between the smartphone data and the other two systems as well. However, between some of the variables of sensor system and the force plate even strong or very strong correlations were found. Other studies also describe the analysis with an iPod touch as an acceptable method for assessing gait in rheumatic patients (Yamada et al., 2012) or as a potentially good opportunity for future use in the clinic (Ellis et al., 2015). The latter study used an ANOVA to define effect sizes that were captured by either Group, Task or Device. They found small or negligible effect sizes for most of the variables for Device, indicating that group effects or task effects were not significantly influenced by the type of device which was used (iPod touch versus heel-mounted footswitches and a GAITRite™ sensor walkway).

### *5.2.2 Handling and Ease of Use of the Systems*

The force plate, as the most commonly used systems for gait analysis, has its advantages mainly in the straightforwardness: Once the plates are set up and connected, there is not much more to do than starting the recording and letting the participant walk across the plate. However, the force plates are usually designed for performing normal gait and turns, sometimes for backward gait. When performing unusual gait tasks, as the tandem gait, the software does not always recognize the feet correctly, leading to shorter periods that are available for analysis. Moreover, the software automatically creates gait reports including the most important gait parameters, which simplifies the evaluation.

Xsens MVN is a simple and user-friendly system, managed via a graphical user interface and live transmission of the sensor data to create an avatar of the participant. This simplifies the search for errors that might occur during the measurement: e.g. if the calibration did not work properly, body segments of the avatar are displayed in an unnatural position or are spinning around. Additionally, the avatar provides an interesting and often motivating insight for the participant into the technical background of the measurement. While set-up and preparation take more time compared to the force plate, a more individualized and detailed evaluation can take place when using the resulting raw data. Raw data of the force plate could be used as well, but only display force data over time. The Xsens data, on the contrary, include calibrated and smoothed sensor data (position, acceleration, orientation) of all segments and therefore allow manifold analyses.

The smartphone apps were easy to install and to handle and also have a simple and user-friendly interface. In the beginning, some smartphones had technical problems, so that the questionnaires could not be presented to the participants, but this could be solved soon. Answering questionnaires on the smartphone seems to be convenient, as participants could choose the time of answering to fit their daily schedule and as resources (i.e. paper) can be saved. Measuring gait and balance at home seems to be convenient for the same reasons, but have the disadvantage that the execution of the exercises cannot be controlled and is therefore more prone to error.

# 6 Conclusion and Outlook

Our analysis has shown that measuring gait and balance in healthy adults with wearable devices, such as smartphones, produces comparable, but somewhat less clear results compared to measuring with a force plate or a sensor system. While there is already a good agreement for the normal gait, adjustments may have to be made in the data evaluation for the other types of gait task investigated in this study to achieve better agreement. We hypothesized that an improvement in gait and balance performance, as well as in the questionnaire scores, would occur between the first and second study visit. Indeed, three weeks of gait and balance training positively influenced gait and balance performance: Comparable improvements were found for all three gait analysis systems in gait parameters and less pronounced improvements were found in balance parameters. However, no improvement was found for the questionnaire scores. To ensure that the improvement is indeed the effect of the training and not a test-retest effect, a further study including a control group which does not take part in a training intervention is required.

For future analyses, the number of comparable gait and balance variables could be increased to get a more detailed overview of reference values of healthy adults and to compare these values to patient data (e.g. patients with movement disorders). Ellis et al. (2015) also suggest that many more consecutive steps are required to reliably detect differences in gait performance, i.e. approximately 100 steps or more. This is not possible when using force plates with a limited length, but seems to be an interesting set-up option for further smartphone-based analyses.

# 7 Supplementary Material

## 7.1 Training Protocol

| Unit | Content of the training |
|---|---|
| 1 | Starts in a sitting position on a stable chair. Explanation and execution of the therapeutic sit: Knees and feet are about hip width apart, feet are below the knees and body posture is upright. Warm-up and strength training of the joints: Ankle joint (flexion and extension, single-legged and double-legged, alternating with increasing speed), knee joint (flexion and extension), hip joint (flexion and extension with increasing speed, adduction and abduction, raising one or both legs). More demanding: Using a Thera band (elastic band)/loop or a Swiss ball (exercise ball) to sit on. |
| 2 | Starts in a sitting position on a stable chair, voluntarily an additional air pad or blanket can be put on the surface to increase the difficulty. Tasks from the first unit are repeated. New tasks: Raising both legs (core strength and balance), moving a ball (or e.g. bottle of water/...) from side to side, circling the ball around the knees and around the body, throwing and catching the ball in different ways (core stability, coordination). |
| 3 | Starts in a sitting position on a stable chair, voluntarily an additional air pad or blanket can be put on the surface. Tasks from the first unit are repeated shortly. Coordination training: Alternating foot tapping with different speed, combined with alternating hand flexion and extension. Rabbit and Hunter (on one hand the index and middle finger are extended, like a "peace" sign or like the ears of a rabbit, on the other hand, thumb and index finger are extended, like a gun. The two signs shall be switched between the two hands as fast as possible, with the gun always pointing at the rabbit), finger tapping tasks (tip of the thumb touches the tips of each other finger of one hand, back and forth, the other hand performs the same task in the reverse way). Demonstration and execution of different stance variations. Exercises with the Thera band in those stances (strength and balance).   |
| 4 | Starts in a standing position, preferably barefoot on a solid ground. Repetition of the stance variations. Exercises with the Thera band in those stances, increased difficulty by performing one-sided exercises (strength and balance). Stance variations with eyes closed (balance) and with core rotations (strength and balance). Preparation for single leg stance: Weight distribution towards one leg, other leg moves on the ground (balance). |
| 5 | Starts in a standing position, preferably barefoot on a solid ground. Extension of stance forms with exercises: Same tasks in more demanding stances (e.g. tandem stance), gaze follows the arms while moving them (strength, balance). Preparation for single leg stance: Weight distribution towards one leg, other leg leaves the ground and moves in different directions (balance). Single leg stance: Foot floats above the ground, moves back and forth / sideways, foot is at the knee, then moves, arms are then crossed behind the back while moving the feet. |

| Unit | Content of the training |
|---|---|
| 6 | Starts in a standing position, preferably barefoot on a solid ground. Repetition of the single leg stance exercises. Single leg stance with a threefold right angle: Hip joint, knee joint, ankle joint and with a swinging leg (balance). Normal gait: Conscious rolling motion of the feet and stable arch of foot. Backward gait. Gait on the heels and gait on the toes, both forwards and backwards (gait, coordination).  |
| 7 | Starts in a standing position, preferably barefoot on a solid ground. Repetition of different forms of gait. Gait on the medial and lateral foot edge. Dynamic gait (exaggerated push-up at toe-off phase). Gait with short breaks in the single leg stance phases, forwards and backwards, then additionally raising to the toes in the single leg stance phases as a progression. Sideward gait, sideward gait with cross-over steps. Tandem gait forward and backwards. Gait forms with eyes closed (gait, coordination). |
| 8 | Starts in a standing position, preferably barefoot on a solid ground. Repetition of tandem gait, eyes open and closed. Sideward gait in a more tucked position and with a Thera band/loop around the knees, lunges with careful attention to the leg axis (strength, gait). Single leg stance: Threefold right angle, circling a ball / water bottle around the body and around the upper leg, improving from fixed gaze to moving gaze (balance).  |
| 9 | Starts in a standing position, preferably barefoot on a solid ground. Single leg stance exercises: Gaze moves through the room, gaze follows the hand while hand moves from the front to the side of the body. Single leg stance on unstable ground (e.g. air pad, blanket): normal stance, dynamic stance with upper leg moving, ankle joint flexion and extension (balance). Foot mobility, stretching of hip flexor and leg extensor (mobility). |
| 10 | Starts in a standing position, preferably barefoot on a solid ground. Repetition of single leg stance exercises. Increasing difficulty by increasing movement amplitudes (range of motion) and by combining exercises with an unstable ground. Rabbit and Hunter task and finger tapping task while standing in a tandem stance. Lunges with turning the body sideways, stretching of leg flexors (mobility). |
| 11 | Starts in a standing position, preferably barefoot on a solid ground. Single leg stance, threefold right angle, legs and arms swing, head is turned sideways (balance, coordination). Small jumps: From stance to single leg stance, jumping sideways and backwards, with increasing jump distance (strength, balance). Stretching of calves and leg extensors, mobilization of joints. |
| 12 | Starts in a standing position, preferably barefoot on a solid ground. Repetition of small jumps. Single leg jumps: forwards, backwards, with turns (strength, balance). Gait and running drills: normal gait forwards and backwards, ankle work (fast alternating rolling motion of both feet), skippings, skippings with coordination exercises (e.g. two times one side, one time other side). |

## 7.2 Data extraction Xsens

The data were recorded with the Xsens MVN 2020.2 software and saved in a “*.mvn*” format. Afterwards, the data were converted from the “*.mvn*” to a “*.mvnx*” format within the software itself, which is necessary for further data processing. Finally, a python script was used to extract the position of feet and pelvis from the data and to save it in a “time x position” data frame in a “*.txt*” file.

The following script for gait tasks and balance tasks serves as an overview of feature extraction, in a way that makes it understandable and reproducible for outsiders.

### *7.2.1 Gait Tasks*

```
8   import numpy as np
9   import matplotlib.pyplot as plt
10
11  ########### LOAD COM DATA ############################################
12  data = np.loadtxt('214329-001-NormalerGang_Seg_RightFoot_LeftFoot_Pelvis_Data_position_orientation.txt
13
14  timeframes = data[:,1]
15  time = timeframes / 60
16  COM_x = data [:,14] #sagittal / anterior posterior
17  COM_y = data[:,15] # right left
18  COM_z = data[:,16] # vertical / up down
19  LeftFoot_x = data [:,17]
20  LeftFoot_y = data [:,18]
21  LeftFoot_z = data [:,19]
22  RightFoot_x = data [:,20] #front-back in m
23  RightFoot_y = data [:,21] #left-right
24  RightFoot_z = data [:,22] #height
25
26  plt.axis('equal')
27  plt.plot(LeftFoot_x, LeftFoot_y)
28  plt.axis('equal')
29  plt.plot(RightFoot_x, RightFoot_y)
30  plt.axis('equal')
31  plt.plot(COM_x, COM_y)
32  plt.plot(time, LeftFoot_y, time, COM_y, time, RightFoot_y)
```

**(12-24) Data import.** Data were loaded into the *Anaconda Spyder* software (python 3.8) and columns were assigned to the corresponding variables. The pelvis data are defined as center of mass (*COM*) in x-direction (anterior-posterior), in y-direction (medial-lateral) and in z-direction (vertical). The definition of axes also applies to the data of the left and right foot (*LeftFoot*, *RightFoot*).

**(26-32) Visual check.** Data was visualized to check it for plausibility and to avoid including errors.

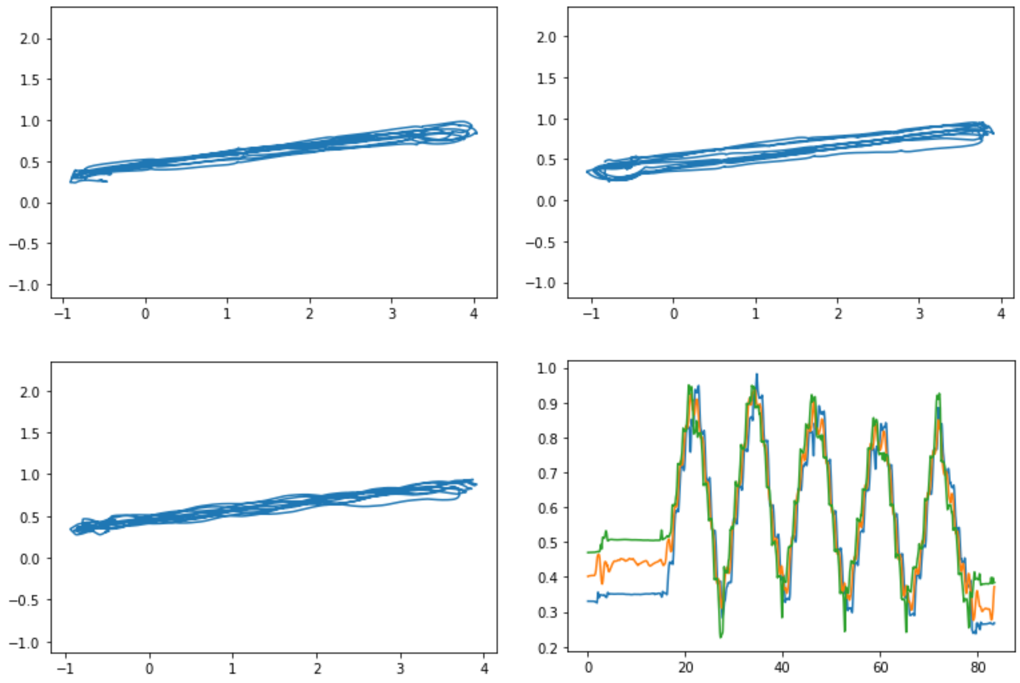
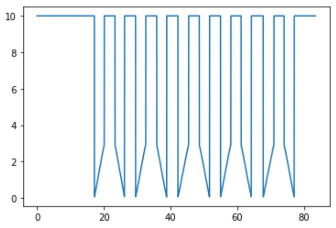


Fig. 8: Output. Top left: Position of the left foot; top right: position of the right foot, bottom left: position of the center of mass, bottom right: position of left foot, right foot and COM over time. In all four plots, the x-axis describes anterior-posterior motion and the y-axis describes the medial-lateral motion.

```
39 ########## CALCULATE TIME AT GAIT PLATE ################################
40
41 maxCOMx = max(COM_x)-1
42 minCOMx = min(COM_x)+1
43
44 import copy
45 COM_x_new = copy.copy(COM_x)
46 COM_x_new[COM_x_new > maxCOMx] = 9.999
47 COM_x_new[COM_x_new < minCOMx] = 9.999
48 COM_x_new_time = np.array([time] + [COM_x_new])
49 plt.plot(COM_x_new_time[0,:], COM_x_new_time[1,:])
```

**(41-49) Data cut.** The original data contains turns at the end and at the beginning (most anterior and most posterior point, x-axis) of each lane. As the participants walked on the force plate in the laboratory, they performed the turn at the same position after every lane, that is, right after they left the force plate. This makes it easy to exclude the turns from the original data and to separate the lanes from each other: In this approach, the first and last meter in the x-direction was first replaced by the value "9.999" and then subtracted from the data (in this case: COM_x).



| | 1027 | 1028 | 1029 | 1030 | 1031 | 1032 |
|---|---|---|---|---|---|---|
| 0 | 17.1167 | 17.1333 | 17.15 | 17.1667 | 17.1833 | 17.2 |
| 1 | 9.999 | 9.999 | 9.999 | 0.069642 | 0.081671 | 0.094027 |

Fig. 9: The plot on the left side displays the COM position in x-direction (m) over time (s). Since the first and last meter have been cut out of the data, the x-position jumps to 9.999 at the beginning and the end of each lane. On the right side the underlying table is shown, according to which the time frames for each participant were manually inserted into the script.

This result is the output shown in Fig. 9, which is described by an example excerpt next to it. Both in the figure and in the table the time is given in seconds (x-axis / row 0) and the position in x-direction in meters (y-axis / row 1). The table serves as a basis for splitting the original data into individual lanes. The first number in line 1 (x-position) that is not equal to “9.999” (in this case: column 1030) corresponds to the starting point of the first lane. The values of the x-position then increase until “9.999” is reached again and thus the end of the first lane. This is repeated until all six lanes (normal gait and backward gait) or four lanes (tandem gait) are defined by their start and end indices.

```
COM_x_Lane1 = COM_x_new_time[:,1030:1207]
COM_x_Lane2 = COM_x_new_time[:,1401:1570]
COM_x_Lane3 = COM_x_new_time[:,1771:1952]
COM_x_Lane4 = COM_x_new_time[:,2151:2329]
COM_x_Lane5 = COM_x_new_time[:,2532:2723]
COM_x_Lane6 = COM_x_new_time[:,2916:3099]
```

It follows that each axis is divided into six (four) lanes for COM and for feet, which are used for further analysis.

```
115    plt.axis('equal')
116    plt.plot(LF_x_Lane1, LF_y_Lane1)
117    plt.axis('equal')
118    plt.plot(RF_x_Lane1, RF_y_Lane1)
119    plt.axis('equal')
120    plt.plot(COM_x_Lane1[1,:], COM_y_Lane1[1,:])
```

**(115-120) Visual check.** Again, COM, left foot (LF) and right foot (RF) positions are checked visually for inconsistencies (see figure x, which shows a single lane as an example).

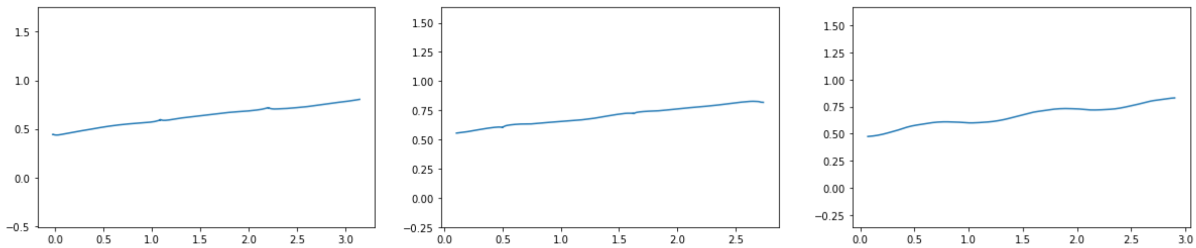


Fig. 10 shows the left foot, right foot and COM, respectively. In all three plots, the position in the x-direction is shown on the x-axis and the position in the y-direction is shown on the y-axis.

As can be seen in Fig. 10, the sensors of the Xsens system are subject to deviation, so that after a few lanes of walking the direction of travel does not perfectly match the direction of the x-axis anymore. However, to obtain the most accurate results, the data is rotated to maximize the conformance between the walking direction and the x-axis.

```
132 Testline_Lane1 = []
133 Testline_Lane1 = np.array([COM_x_Lane1[1,:]] + [COM_y_Lane1[1,:]])
134 Line_Lane1 = np.array([Testline_Lane1[:,0]] + [Testline_Lane1[:,-1]])
135 LL1 = Line_Lane1[1,:] - Line_Lane1[0,:]
136 plt.axis('equal')
137 plt.plot(Line_Lane1[:,0], Line_Lane1[:,1])
138 plt.plot(COM_x_Lane1[1,:], COM_y_Lane1[1,:])
```

**(132-138) Data rotation.** In order to achieve this, at first a straight line is laid through the walking path. To start with, an array is created, that comprises both x- and y-data of the corresponding lane. From that array, only the first and last data point ([:,0] accesses the first data point and [:,-1] accesses the last data point) are copied into a new array (Line_Lane1), which mainly serves the visualization of that calculation (see blue line in Fig. 11). The actual line data is then given in LL1, which is the subtraction of start and end position.

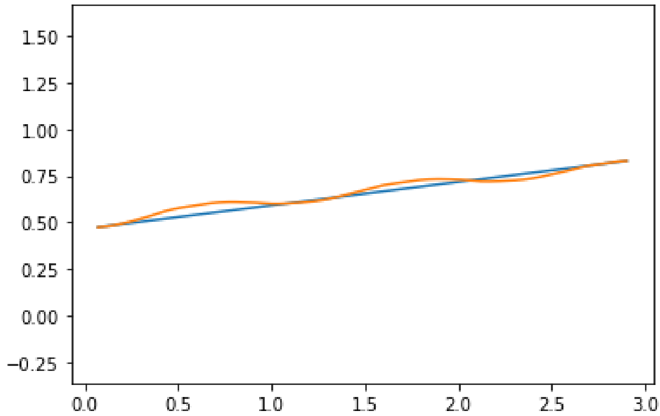



Fig. 11: The COM position is displayed again in orange (x-position on the x-axis, y-position on the y-axis). Additionally, the blue line represents the line that was laid through the data for calculation of the angle between the actual path and the x-axis.

```
141 import numpy.linalg as LA
142 
143 a = np.array([1, 0])
144 b = copy.copy(LL1)
145 
146 inner = np.inner(a, b)
147 norms = LA.norm(a) * LA.norm(b)
148 
149 cos = inner / norms
150 rad = np.arccos(np.clip(cos, -1.0, 1.0))
151 deg = np.rad2deg(rad)
152 print(deg)
```

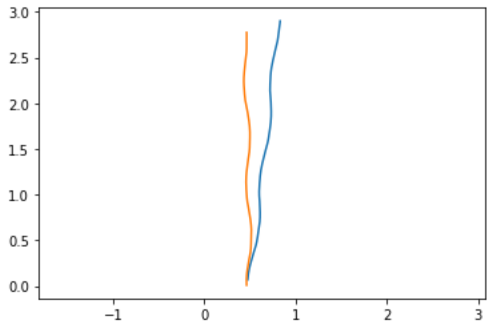
**(141-152) Data rotation.** Afterwards, the angle between the actual x-axis (a) and the calculated line (b = LL1), which describes the actual walking direction of the participant, is calculated with the linear algebra module of NumPy (https://numpy.org/doc/stable/reference/routines.linalg.html).

```
156 theta = np.radians(deg)
157 c, s = np.cos(theta), np.sin(theta)
158 rotation_matrix = np.array(((c, -s), (s, c)))
159 print(rotation_matrix)
160 rot_a = c
161 rot_b = -s
162 rot_c = s
163 rot_d = c
164
165 COM_xy_Lane1 = np.array([COM_y_Lane1[1,:]] + [COM_x_Lane1[1,:]])
166 COM_xy_Lane1tp = COM_xy_Lane1.transpose()
167 plt.axis('equal')
168 plt.plot(COM_xy_Lane1tp[:,0], COM_xy_Lane1tp[:,1])
```

```
186 COM_xy_Lane1tp_new = np.array([(COM_xy_Lane1tp[:,0] * rot_d) - (COM_xy_Lane1tp[:,1] * rot_c)] +
187                               [(COM_xy_Lane1tp[:,1] * rot_a) + (COM_xy_Lane1tp[:,0] * rot_b)])
188
189 plt.axis('equal')
190 plt.plot(COM_xy_Lane1tp_new[0,:], COM_xy_Lane1tp_new[1,:])
```

**(156-168) Data rotation.** With the angle calculated beforehand (*deg*), a rotation matrix is now created to rotate the original vector towards the x-axis (https://scipython.com/book/chapter-6-numpy/examples/creating-a-rotation-matrix-in-numpy/). In a second step, x- and y-axis are transposed. This is to make it easier for people looking at these figures to visualize the direction of walking of the participant (see Fig. 12). This part of the script is repeated for the left and the right foot and for each lane separately (not shown).

(186-190) The final matrix of, in this case, the COM is now created by multiplying the original matrix with the rotation matrix ($x_{rotated}$ = cos(α) * x - sin(α) * y; $y_{rotated}$ = sin(α) * x + cos(α) * y; with x and y being the variables of the original data). Original and new data are plotted and checked for errors. The new walking path should match the x-axis as close as possible (see orange line in figure x, as x- and y- axis have been transposed, it matches the y-axis). Again, this is repeated for the left and the right foot and for each lane separately.




```
In [26]: print(rotation_matrix)
[[ 0.99223025 -0.12441516]
 [ 0.12441516  0.99223025]]
```

Fig. 12 displays how the rotation matrix works (left plot): The blue line again displays the COM position, only this time with the x-position on the y-axis and the y-position on the x-axis, for better visualization of the gait path. The orange line is the corrected path after multiplying the data with the rotation matrix.

```
541 from scipy.signal import find_peaks
542 peaks, _ = find_peaks(COM_z_Lane1[1,:], height=0.84) # check height
543 plt.plot(COM_z_Lane1[1,:])
544 ind = peaks
545 Peaks2D = COM_z_Lane1[:,ind]
546
547 peaks_timeonly = Peaks2D[0,:]
548 peaks_heightonly = Peaks2D[1,:]
549
550 plt.plot(COM_z_Lane1[0,:], COM_z_Lane1[1,:])
551 plt.plot(peaks_timeonly, peaks_heightonly, "x")
552 plt.show()
```

**(541-552) Inter-step time.** To calculate the time between two consecutive steps of the participant, the vertical component of the COM was used. As the COM moves up and down in cyclic movements (see Fig. 13, left), it is easy to use its peaks as markers for a step cycle. Usually and according to definition, one step starts with the heel contact of the first foot and ends with the heel contact of the other foot. However, the length and thus time of a step cycle remains the same, no matter at which phase of the cycle the marker is set, as soon as start and end position are set at the *same* phase of the step cycle. The height to find the peaks (line 542) was adapted for each participant by visually checking the output plots. For more ambiguous curves, as some of the tandem gait curves (see Fig. 1Fig. 13, right) an additional information was added to the script (“width=9”), to define a minimum distance between two consecutive peaks.

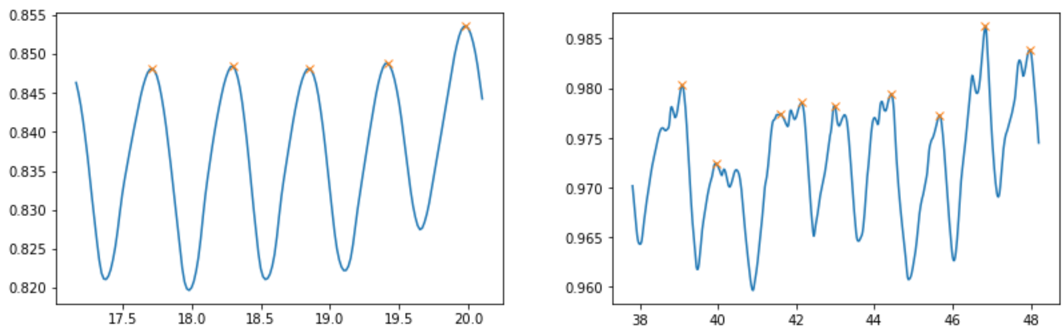



Fig. 13: shows the COM position in z-direction (vertical direction, y-axis) over time (s) in normal gait (left plot) and for a shaky tandem gait (right plot). In most of the cases, peaks were easy to detect, as on the left side.

```
av_data = []
InterStepTime_L1 = 0
for i in range(len(peaks)-1):
    av_data = peaks_timeonly[i+1]-peaks_timeonly[i]
    InterStepTime_L1 += av_data

InterStepTime_L1 = InterStepTime_L1/(len(peaks)-1)
```

```
680 InterStepTime = (InterStepTime_L1 + InterStepTime_L2 + InterStepTime_L3
681 + InterStepTime_L4 + InterStepTime_L5 + InterStepTime_L6) / 6
682
683 Frequency = 1/InterStepTime
684
685 All_InterStepTimes = np.array([InterStepTime_L1, InterStepTime_L2, InterStepTime_L3,
686                                InterStepTime_L4, InterStepTime_L5, InterStepTime_L6])
687
688 import statistics
689 Var_InterStepTime = statistics.variance(All_InterStepTimes)
```

**(560-566, 680-681) Inter-step time.** The time in seconds between two steps (inter-step time) was then calculated by subtracting the times of two neighboring peaks, respectively. This was repeated until reaching the last peak of one lane. All inter-step times of one lane were collected in one array (*e.g. InterStepTime_L1*) and the average inter-step time of that lane was defined. Later on, the average inter-step time in seconds of all six lanes (or four lanes, for the tandem gait) was calculated.

**(683) Step frequency.** The step frequency, that is, how many steps the participant performed per second, was calculated by dividing one by the average inter-step time.

```
695 Variance_COMy_L1 = statistics.variance(COM_xy_Lane1tp_new[0,:])
696 Variance_COMy_L2 = statistics.variance(COM_xy_Lane2tp_new[0,:])
697 Variance_COMy_L3 = statistics.variance(COM_xy_Lane3tp_new[0,:])
698 Variance_COMy_L4 = statistics.variance(COM_xy_Lane4tp_new[0,:])
699 Variance_COMy_L5 = statistics.variance(COM_xy_Lane5tp_new[0,:])
700 Variance_COMy_L6 = statistics.variance(COM_xy_Lane6tp_new[0,:])
701
702 Variance_COMy = (Variance_COMy_L1 + Variance_COMy_L2 + Variance_COMy_L3 +
703 Variance_COMy_L4 + Variance_COMy_L5 + Variance_COMy_L6) / 6
```

**(695-703) Left-Right-Variance.** In this step, the variance across all y-values (medial-lateral) was calculated for each lane separately and then averaged across all lanes. The less the COM of the participant deviates from the x-axis, the closer the value is to zero.

```
710 v_Lane1 = abs((COM_xy_Lane1tp_new[1,-1]-COM_xy_Lane1tp_new[1,0])/(COM_x_Lane1[0,-1]-COM_x_Lane1[0,0])
711 v_Lane2 = abs((COM_xy_Lane2tp_new[1,-1]-COM_xy_Lane2tp_new[1,0])/(COM_x_Lane2[0,-1]-COM_x_Lane2[0,0])
712 v_Lane3 = abs((COM_xy_Lane3tp_new[1,-1]-COM_xy_Lane3tp_new[1,0])/(COM_x_Lane3[0,-1]-COM_x_Lane3[0,0])
713 v_Lane4 = abs((COM_xy_Lane4tp_new[1,-1]-COM_xy_Lane4tp_new[1,0])/(COM_x_Lane4[0,-1]-COM_x_Lane4[0,0])
714 v_Lane5 = abs((COM_xy_Lane5tp_new[1,-1]-COM_xy_Lane5tp_new[1,0])/(COM_x_Lane5[0,-1]-COM_x_Lane5[0,0])
715 v_Lane6 = abs((COM_xy_Lane6tp_new[1,-1]-COM_xy_Lane6tp_new[1,0])/(COM_x_Lane6[0,-1]-COM_x_Lane6[0,0])
716
717 Speed = (v_Lane1+v_Lane2+v_Lane3+v_Lane4+v_Lane5+v_Lane6)/6
```

**(710-715) Velocity.** Velocity was calculated separately for each lane by subtracting the first from the last data point for both position and time, and then dividing position by time. After that, the average velocity was calculated.

```
722 peaks, _ = find_peaks(LF_z_Lane1, height=0.17)
723 plt.plot(LF_z_Lane1)
724 ind = peaks
725 x_values = LF_xy_Lane1tp_new[1,ind]
726
727 Stride = 0
728 Stride_length = []
729 for i in range(len(peaks)-1):
730     Stride = x_values[i+1]-x_values[i]
731     Stride_length.append(Stride)
732 Stride_length_new = abs(np.hstack(Stride_length))
```

```
879 Av_Stride_length = np.mean(Stride_length_new) # Average Stride Length
880 Var_Stride_length = statistics.variance(Stride_length_new) # Variance
```

**(722-732, 879-880) Stride length.** One stride, which is a cycle of two steps, starts by definition with the heel contact of one foot and ends with the heel contact of the same foot. To calculate the stride length in meters, the vertical axis of one foot (e.g. left foot, Fig. 14) was plotted and its peaks were marked and extracted. The absolute value of the difference of position (x-axis) was added to an array, which in the end contained the values of all lanes and both feet. Out of these collected values, the average stride length and the variation of the stride length were calculated. The height to find the peaks (line 722) of the foot position was adapted for each participant by visually checking the output plots.

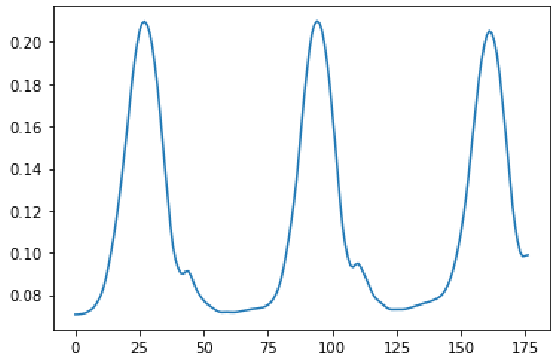



Fig. 14 displays the path of one foot in z-direction (vertical direction), including the z-position in meters on the y-axis and the data frames on the x-axis.

```
892 RF_z_Lane1_2 = RF_z_Lane1*-1
893 plt.plot(RF_z_Lane1_2)
894 peaks, _ = find_peaks(RF_z_Lane1_2, height=-0.09, width=9) #!# width & height
895 ind = peaks
896
897 yPos_right = []
898 for i in ind:
899     yPos_right.append(RF_xy_Lane1tp_new[0,i])
900 yPos_right2 = np.array(yPos_right) #Array of y-position right foot
```

```
913 Step_width = []
914 for i in range(min(len(yPos_right2), len(yPos_left2))):
915     Step_width.append(abs(abs(yPos_right2[i]) - abs(yPos_left2[i])))
916 Step_width_abs = np.hstack(np.array(Step_width)) #absolute values
```

```
1048 Step_width = sum(Step_width_abs) / len(Step_width_abs) #average value
1049 var_Step_width = statistics.variance(Step_width_abs)
```

**(892-900, 913-916, 1048-1049) Step width.** To calculate how wide the steps of the participants were, the vertical z-axis and the y-axis (medial-lateral displacement) of the feet were considered. The time frame with the lowest foot position of each foot (mid-stance phase, Suppa et al., 2020) is marked by searching for the minima in z-direction (vertical axis, see line 894). Its position in y-direction at the same time frame (line 899) is used to determine the distance between left and right foot (line 915). This is repeated for all lanes and added up to one array. Height and width (line 894) are adapted individually for each participant. Finally, an average value and the variation of the step width is calculated.

```
1077    plt.plot(LF_z_Lane1)
1078    peakscomz1, _ = find_peaks(LF_z_Lane1, height = 0.18)
1079    ind = peakscomz1
1080    Peakscomz12D = LF_z_Lane1[ind]
```

```
1102    LF_height_Lane1 = np.mean(Peakscomz12D) - np.min(LF_z_Lane1)
1103    LF_height_Lane2 = np.mean(Peakscomz22D) - np.min(LF_z_Lane2)
1104    LF_height_Lane3 = np.mean(Peakscomz32D) - np.min(LF_z_Lane3)
1105    LF_height_Lane4 = np.mean(Peakscomz42D) - np.min(LF_z_Lane4)
1106    LF_height_Lane5 = np.mean(Peakscomz52D) - np.min(LF_z_Lane5)
1107    LF_height_Lane6 = np.mean(Peakscomz62D) - np.min(LF_z_Lane6)
1108    LF_height_av = (LF_height_Lane1 + LF_height_Lane2 + LF_height_Lane3 +
1109    LF_height_Lane4 + LF_height_Lane5 + LF_height_Lane6) / 6
```

**(1077-1080, 1102-1109) Foot elevation.** Finally, the maximum elevation of each foot in every step is calculated by considering the z-axis (vertical direction). Therefore, all peaks of a foot are marked and its values are added up in one array. This is done separately for the left and the right foot and for each lane. The actual elevation height is determined by subtracting the minimum height of each lane from the mean height, as the sensor is on top of the foot and the participants feet have different shapes and heights.

```
import pandas as pd

df = pd.DataFrame([["Step_Frequency",Frequency], ["Av_Step_Length",Av_Step_length],
                    ["Var_Step_length",Var_Step_length], ["Inter_Step_time",InterStepTime],
                  ["Var_InterStepTime",Var_InterStepTime], ["Speed",Speed],
                  ["Var_COMy",Variance_COMy], ["Step_width", Step_width],
                  ["LF_height", LF_height_av], ["RF_height", RF_height_av]])
datatoexcel = pd.ExcelWriter("NormalGait.xlsx", engine='xlsxwriter')
df.to_excel(datatoexcel, sheet_name= '214329')
datatoexcel.save()
```

All variables were then saved in an excel format.

### 7.2.2 Balance Tasks

Data import was performed in a similar way as described for the gait tasks and data were also checked visually for plausibility.

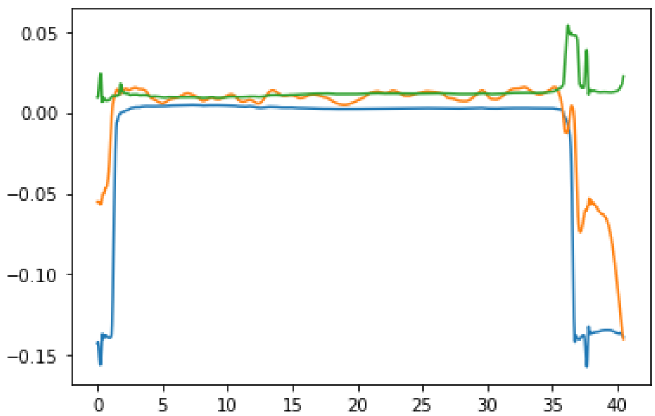



Fig. 15: Position of the left foot (green), right foot (blue) and center of mass (orange). The y-position in meters is given on the y-axis and the time in seconds on the x-axis.

```
44      COM_x_stance = COM_x_new_time[:,480:1860]
45      COM_y_stance = COM_y_time[:,480:1860]
46      COM_z_stance = COM_z_time[:,480:1860]
47      LF_x_stance = LeftFoot_x[480:1860]
48      LF_y_stance = LeftFoot_y[480:1860]
49      LF_z_stance = LeftFoot_z[480:1860]
50      RF_x_stance = RightFoot_x[480:1860]
51      RF_y_stance = RightFoot_y[480:1860]
52      RF_z_stance = RightFoot_z[480:1860]
53
54      stancetime = abs(COM_x_new_time[0,480] - COM_x_new_time[0,1860])
55      COM_x_only = COM_x[480:1860]
56      COM_y_only = COM_y[480:1860]
57      COM_z_only = COM_z[480:1860]
58
59      plt.axis('equal')
60      plt.plot(LF_x_stance, LF_y_stance)
61      plt.axis('equal')
62      plt.plot(RF_x_stance, RF_y_stance)
63      plt.axis('equal')
64      plt.plot(COM_x_stance[1,:], COM_y_stance[1,:])
```

**(44-57) Data cut.** For each participant the time span for analysis was selected in a way that movements in the beginning or at the end of the balance task were excluded. Analysis was performed on the COM data only, however, left and right foot data were still included and shown for better visualization.

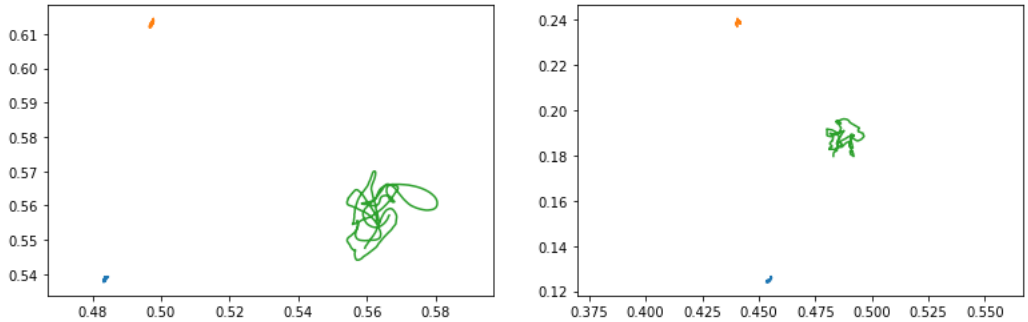



Fig. 16: Position of left foot (blue), right foot (orange) and center of mass (green) during the narrow stance with eyes closed (left) and eyes open (right). Position in x-direction is given on the x-axis, position in y-direction is given on the y-axis.

```
from math import sqrt

n = len(COM_x_only)
x = COM_x_only
y = COM_y_only

def pathlength(x,y):
    n = len(x)
    lv = [sqrt((x[i]-x[i-1])**2 + (y[i]-y[i-1])**2) for i in range (1,n)]
    L = sum(lv)
    return L

Total_Pathlength = pathlength(COM_x_only, COM_y_only)
print(Total_Pathlength)

Path_per_second = Total_Pathlength / stancetime *1000
```

**(69-84) Path.** In the first step of the analysis, the total path length that was travelled by the COM of the participant was calculated (https://stackoverflow.com/questions/20773612/python-compute-the-length-of-a-path-for-a-moving-object). For the length of the dataset, that was cut one step earlier, the path in both x-direction (anterior-posterior) and y-direction (medial-lateral) was added up. The total path length in meter was then divided by the time of analysis, to get comparable data across all participants (*Path_per_second*). This at the same time describes a velocity, i.e. how many millimeters the participant travelled per second (line 84).

```
90    AP_sway = (max(COM_x_only) - min(COM_x_only)) * 1000
91    ML_sway = (max(COM_y_only) - min(COM_y_only)) * 1000
92    # path in mm
93
94    import math
95    ellipse = math.pi * AP_sway * ML_sway
```

**(90-95) Ellipse.** For a second step, the area of an ellipse around the COM path was calculated by simply multiplying the anteroposterior sway and the mediolateral sway with pi. This resulted in an ellipse enclosing all data points and given with an area in $mm^2$.

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