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Combining Accelerometer and GPS Features to Evaluate Community Mobility in Knee Ankle Foot Orthoses (KAFO) Users

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Abstract

Orthotic and assistive devices such as knee ankle foot orthoses (KAFO), come in a variety of forms and fits, with several levels of available features that could help users perform daily activities more naturally. However, objective data on the actual use of these devices outside of the research lab is usually not obtained. Such data could enhance traditional lab-based outcome measures and inform clinical decision-making when prescribing new orthotic and assistive technology. Here, we link data from a GPS unit and an accelerometer mounted on the orthotic

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device to quantify its usage in the community and examine the correlations with clinical metrics. We collected data from 14 individuals over a period of 2 months as they used their personal KAFO first, and then a novel research KAFO; for each device we quantified number of steps, cadence, time spent at community locations and time wearing the KAFO at those locations. Sensor-derived metrics showed that mobility patterns differed widely between participants (mean steps: 591.3, SD =704.2). The novel KAFO generally enabled participants to walk faster during clinical tests (6Minute-Walk-Test=71.5m, p=0.006). However, some participants wore the novel device less often despite improved performance on these clinical measures, leading to poor correlation between changes in clinical outcome measures and changes in community mobility (6Minute-Walk-Test – Community Steps: r=0.09, p=0.76). Our results suggest that some traditional clinical outcome measures may not be associated with the actual wear time of an assistive device in the community, and obtaining personalized data from real-world use through wearable technology is valuable.

Keywords

Wearable sensor; accelerometer; GPS; rehabilitation; assistive device; orthosis

I. Introduction

IN RECENT years, the fields of prosthetics and orthotics have seen the development of technologically advanced devices that promise to improve function in people with lower limb impairments. Advancements in computing power, lightweight materials, and miniaturized sensors and actuators have fueled the development of novel devices for personal mobility. These include both microprocessor controlled-passive and powered approaches to prostheses and orthoses, with features that are meant to restore a more natural gait pattern, and help users perform functional activities more efficiently [1]-[3].

While technologically advanced assistive devices can bring significant improvements to patients' quality of life, there is still a lack of knowledge of their actual usage in everyday life. Traditional self-report surveys [4]-[7] are used to gain an understanding of whether a patient prefers using a new device over their traditional device. In addition, clinicians and engineers use standardized clinical outcome tests, such as the 10-meter walk test (10mWT) or the 6-minute walk test (6MWT), to measure performance of a particular device for an individual within a clinical/research setting. However, objective and quantitative data on how frequently somebody will actually use a new assistive/orthotic device in the community, and which functional activities will be enabled by it, is critical to facilitate reimbursement by health insurance companies, given the high market cost that such assistive technology typically have.

On the other hand, it is now possible to obtain large amounts of personal mobility data from cheap personal wearable devices, such as activity and Global Positioning System (GPS) trackers, as well as smartphones. Personal devices can easily and unobtrusively collect information on locations visited, number of steps or types of physical activities performed [8], [9], and are increasingly used in healthcare and rehabilitation [10]-[12]. Given that

such data can be collected continuously, these approaches open up new possibilities to study how people with disabilities move in the community [13] or use their device [14], and therefore can provide insights into which factors drive the actual adoption of different assistive devices.

Recent studies explored the use of wearable and mobile technology, including iPods [15], to track usage of assistive devices such as wheelchairs [16] and prostheses [17], [18], as well as functional capabilities in lower limb amputees [19]. GPS sensors have been used to follow mobility patterns of individuals with disabilities [20], [21], as well as in combination with wearable accelerometers to examine number of community steps taken by amputees with different levels of mobility [22]. Most of these studies highlighted the utility of objectively monitoring assistive device usage [23]; for example, measuring wear time of KAFOs in children with Cerebral Palsy [24] showed that parent-reported wear times differed significantly from sensor-based measurements, confirming the importance of obtaining objective data to quantify device usage.

While these methods have been applied to a variety of clinical populations, they have yet to be fully explored to advance knowledge of orthotic devices usage. Specifically, wearable technology could be used to compare the efficacy of different orthotic devices, by directly measuring their use in the community.

In the current study, we harnessed the availability of wearable sensor technology to study the community usage of KAFOs when participants used their personal KAFO and then a novel research KAFO. Using an activity tracker (accelerometer) mounted on the KAFO and a GPS unit worn by the participants, we tracked when each assistive device was used and where. We compared mobility patterns in a cohort of 13 individuals, as they used their personal KAFO and a novel research KAFO device over a total period of 2 months. We derived 4 metrics from the combined GPS and accelerometer data to measure the amount of usage and walking performed with each KAFO. We then measured the correlations between the community mobility metrics and standardized clinical outcome measures, to understand whether the sensor metrics complement the information collected during clinical visits, as a mean to understand community usage of different KAFOs.

II. Methods

A. Experimental Design

A total of 18 participants provided informed consent and were enrolled in this Northwestern University IRB approved study, which aimed at understanding the impact of a computer controlled KAFO on personal mobility. The study inclusion criteria included active use of a unilateral KAFO for impairment: all participants in the study regularly used a unilateral orthosis (KAFO) for ambulation, as a result of neurological injury, traumatic injury, or neuromuscular disease (see Table I).

KAFOs are devices that provide increased stability to the knee and below and can have multiple types of knee joints. Traditional, locked KAFOs block knee movement during both the swing and stance phase; they provide the most stability but are biomechanically

and metabolically inefficient [25], [26]. Stance control orthoses (SCO) are an alternative to traditional locked KAFOs. SCOs are a version of KAFOs that allow the knee to flex during swing phase to allow a more natural and efficient gait pattern, but may also be less versatile, leading to safety concerns on uneven terrain. The novel research device was an advanced KAFO that used on-board sensors to provide variable dampening throughout the gait cycle. Sensor-based dampening during stance and swing phase potentially allows for better joint protection, stability, balance especially during walking on uneven terrains, stairs, and ramps. The device was tested in the lab and then provided to participants to assess its use in the community.

The data collection consisted of activity monitoring during community use of the KAFO, followed by a clinical evaluation. These phases were undertaken first for the personal KAFO, and then for the novel one (Fig. 1). Specifically, the first data collection involved monitoring the usage of the personal KAFO used by the study participants regularly in their lives over the course of 1 month (Remote monitoring trial – Fig. 1). Participants were instructed to use their KAFO device as they typically do in their everyday routine. This phase provided a *baseline* against which to compare the usage of the novel KAFO in the second part of the experiment. Following the remote monitoring trial with their personal KAFO, participants returned to the lab where they underwent a series of clinical outcome tests (Clinical Eval – Fig. 1) which included a 6-minute walk test (6MWT) and a 10-meter walk test at self-selected speed (10mWT_ss or 10mWT as abbreviated below), which are clinical measures of walking speed and endurance [27]-[29]. Participants also reported their satisfaction, as well as improvements in quality of life with the KAFO by completing the Orthotic and Prosthetic Users' Survey (OPUS) [30], which is a self-report questionnaire consisting of multiple modules.

Following the first data collection, participants were fitted for the novel KAFO. After that, they received 6 training/acclimatization sessions of 1-hour each, spaced by about 1 week (Training Visits - Fig. 1) by a trained clinician on how to use the novel KAFO, prior to starting the second remote monitoring trial with the novel KAFO. During this period, participants were instructed to use the novel KAFO for their typical everyday functional activities. Finally, participants returned to the lab where they underwent the same clinical outcome evaluations, this time using the novel KAFO.

The activity monitoring employed 2 sensors: all participants had their personal KAFO instrumented with an Actigraph wGT3X-BT activity monitor (Actigraph corp., Pensacola, FL). The Actigraph is a tri-axial wearable accelerometer, which was used to record accelerations at a frequency of 30 Hz and was used to determine when a KAFO was worn, and the number of steps taken with the KAFO. The Actigraph was placed as proximal as possible on the thigh shell of the KAFO, along midline (Fig. 1); the position was chosen to maintain security during the remote trial. In addition, each participant was given a lightweight GPS data logger (QStarz International, BT-1000XT), which was worn around the waist and recorded the subject's geographic location every 10 seconds (0.1 Hz sampling rate) to the local memory of the device (Fig. 1). Less than 1% of the data contained dropped samples or early samples. Portable GPS units like this are useful for their accuracy (within 3 meters) and constant sampling rate, have shown reliability and validity in their spatial

accuracy for outdoor movement and are used often in physical activity and transportation research [31].

Participants were asked to wear the GPS unit throughout the course of their day and charge it overnight.

Of the 18 participants enrolled, only 13 (5F; mean age = 54) were included in this analysis (Table I). Specifically, four participants had a relatively lower number of average GPS hours per day (<5) than the rest (>9 hours/day); these participants were thus excluded due to their sparse GPS data recordings. A fifth participant had to be excluded because the Actigraph failed to record any data for one of their trials.

B. GPS and Actigraph Data

Once the GPS data loggers were returned, the GPS data was analyzed using the mapping software ArcGIS (Esri, Redlands, CA): data recordings were divided into days, and then the times at which the participant left and arrived at destinations during each day were identified. Destinations were identified using kernel density tools in ArcGIS. Based on this analysis, each GPS data point was classified into one of three categories: *Inside/Around-Home*, *Trip* or *Community*. *Inside/Around Home* destinations were identified as all GPS points clustered around the location where participants spent the night. A *community* destination was designated by a cluster of 30 points (i.e., 5 minutes sampled at 0.1 Hz) within 50 ft of each other. *Trips* were identified by all other points not belonging to a community or home cluster. To identify any visit potentially missed by this method, we manually inspected each person's day and examined any clusters of points that were labelled as trips but could have been short stops. Clusters that were not by a street light/stop sign were examined in more detail to determine if they were destinations of less than five minutes, such as a gas station or drive-thru food restaurants.

The final output was an analytic data set of time periods labeled as one of the 3 categories, aiding us to quantify time spent in each. We limited our analysis to community locations, since we were interested in analyzing usage of the device outside the home. GPS data classified as Trip were excluded from this analysis, as movement in a vehicle could be misconstrued as wear time. Vehicle trips accounted for the majority (98.5%) of all trips in our dataset, with only 1.5% of these being walking trips.

Actigraph data was downloaded and analyzed using the proprietary software Actilife 6.13. We used the 'Wear Time Validation' feature to detect time periods when the activity monitor was not worn using the Choi algorithm with default settings. This algorithm identifies non-wear periods based on acceleration counts over 1-minute periods, with non-wear labels applied to each 1-minute period with a count of zero that comprises part of a 90-minute window of continuous zero counts, with an allowance for period of up to two minutes with non-zero counts in the 90-minute window if the 30-minute windows before and after each such period have only zero counts [32]. This approach was used to determine when each participant wore the assigned brace during the recording session. The output of this algorithm was a table listing the start and end of each period of identified wear or non-wear, to a resolution of one minute. All times within the recording range of the file were assigned

to one of these two categories. The Actilife software (Actigraph LLC, Pensacola, FL) was also used to obtain the step count for every 10-second epoch when the KAFO was worn. To identify steps, the algorithm implemented in Actilife computes the instantaneous acceleration norm. The algorithm counts steps in epochs of 10 seconds by identifying peaks in the signal with a threshold range. The thresholds are dynamically modified based on the signal frequency within that epoch. Previous studies using the Actigraph device on the lower limb have found reasonable comparison of the outputs of the Actilife algorithm with manual step counts, including for participants with altered gait patterns [33]. Although the Actilife algorithm is proprietary, its behavior under various conditions has been characterized in prior literature [34].

The wear time and step count were finally synchronized with the GPS data, by linking the timestamps from the GPS device and the Actigraph; this allowed determining the proportion of time spent wearing the KAFO device and number of steps taken with it at each visited community location (see “Wear Fraction” below).

C. Mobility Metrics

Based on the linked GPS and Actigraph data we calculated 4 metrics to assess usage and mobility in the community. We reported average values for each participant across all monitoring days:

- *Daily Community Time:* A person may spend time outside their home without necessarily wearing the KAFO for the entire time (e.g., if they are visiting a friend in their home, they might remove the KAFO). As a relative measure of the amount of time spent at community locations, we computed the total time in community locations for every day and averaged the value across all monitoring days. This metric provided an estimate of the time a participant spent outside their home, regardless of whether they are wearing or not the device.
- *Wear Fraction:* In order to get an unbiased estimate of the relative time each participant used a KAFO in the community, we calculated the proportion of time, termed wear fraction (WF), that the device was worn during each community visit; then averaged the values across all visits for each day. and reported the average daily wear fraction. We chose to summarize the wear fraction for each day of recording in this way to assess what proportion of time an individual might be expected to spend using their device at any given visit to a community location.
- *Community Steps:* The Actilife software provided the step count for every 10-second epoch. For each day, we then summed the steps for epochs during visits to community locations to obtain the total steps per day. The reported value is the average daily step count across all monitoring days.
- *Cadence:* We computed cadence (steps/s) for each 10-second epoch containing steps as step count divided by 10 seconds, and then averaged the values across all visits to community locations for each day; we reported the average daily cadence as a proxy for walking speed in the community.

D. Statistical Analysis

To determine how the GPS- and accelerometer-based outcome measures (Mobility Metrics) compare to existing clinical outcome measures, we evaluated the correlations between them using Pearson correlation coefficients. Specifically, we tested whether higher clinical scores with the personal KAFO device are also associated with higher usage of that device in the community. Age and years of experience using the personal KAFO were also included in the correlation analysis. We also tested whether mean clinical and mobility metrics changed significantly when participants used the novel KAFO, relative to the metrics measured with the personal KAFO (baseline). Wilcoxon signed-rank tests were used in place of t-tests when the distribution of the data were not normal. The Shapiro-Wilk test was used to evaluate normality of the data distribution. Significance level was set to 0.05. Python 3.7 was used to perform the data analysis.

III. Results

A. Community Mobility With Personal KAFO

First, we sought to understand how participants used their personal device in the community (Fig. 2). Mean daily steps in the community across all participants varied substantially (**Steps**: 591.3, $SD=704.2$), with one participant being very active community walker and taking an average of more than 2500 steps per day, while others staying close to 0. Mean cadence instead was similar across the group (**Cadence**: 0.30 steps/s, $SD=0.08$). Participants wore their device for an average of 79% of the time while being in the community (**Wear Fraction**: 0.79, $SD=0.30$), and spent outside an average of 4h per day (**Time Community**: 3.83h, $SD=3.01$); again individual variation was wide, with some individuals spending as many as 12h, or as low as 1h daily.

B. Correlations of Clinical Outcome Measures With Community Mobility Metrics

Given the variation in community metrics between individual participants when using their personal KAFO, we wished to explore to what extent these metrics also correlated with other factors already in use in clinical practice. We computed the Pearson correlation coefficients between clinical tests (speed, endurance, OPUS questionnaire), demographics (age, years using their personal device), and the 4 mobility metrics derived from GPS and accelerometer data. In particular, these correlations can be used to evaluate the extent to which these clinical tests correlate with direct measurement of community mobility with a KAFO (Fig. 3).

Clinical tests of walking endurance and speed showed a significant correlation with both steps and cadence in the community (**Steps-6MWT**: $r=0.65$, $p=0.015$; **Cadence-10mWT**: $r=0.63$, $p=0.022$), thus confirming that participants who walked faster in the lab also walked more and faster in the community. However, the same clinical tests were not correlated with the proportion of time wearing the device (**Wear Fraction-6MWT** $r=0.09$, $p=0.77$), nor daily time spent at community locations with either device.

The OPUS self-report score also did not show any significant correlation with usage of the device in the community (**OPUS-Wear Fraction**: $r=-0.06$, $p=0.83$; **OPUS-Time**

community: $r=-0.25$, $p=0.40$); indicating that self-reported comfort with the device is not strongly associated with its use in the community. However, the OPUS score showed a significant negative correlation with the clinical walking tests (**OPUS-6MWT:** $r=-0.63$, $p=0.020$; **OPUS-10mWT:** $r=-0.61$, $p=0.028$), as well as cadence (**OPUS-Cadence:** $r=-0.64$, $p=0.020$), suggesting that participants that walked slower also rated their personal device as more comfortable. As expected, clinical walking tests were strongly correlated with each other (**6MWT-10mWT:** Personal: $r=0.91$, $p=0.001$), since participants walking longer distances in the lab were also faster walkers. The complete list of correlation values is provided in Table II (Supplementary Material).

C. Changes in Mobility Metrics Between KAFO Devices

We then asked whether clinical walking tests and mobility metrics changed significantly when participants used the novel KAFO. We measured differences () relative to their personal device (baseline), such that a positive value indicates that the metric increased with the novel KAFO (Fig. 4). Mean daily steps and cadence across participants did not change significantly (**Steps** $=-189.2$, $W=33.0$, $p=0.38$; **Cadence** $=-0.01$ steps/s, $t=0.89$, $p=0.39$); similarly, mean changes in community time and wear fraction were also not significantly altered overall (**Community Time** $=-0.97$ h, $W=29.0$, $p=0.25$; **Wear Fraction** $=-0.13$, $t=1.09$, $p=0.30$). Conversely, the mean distance walked and walking speed measured in the lab by the 6MWT and 10mWT were both significantly higher for the novel device across participants (**6MWT** $=71.5$ m, $t=-3.31$, $p=0.006$; **10mWT** $=0.17$ m/s, $t=-3.04$, $p=0.01$). Thus, the novel KAFO enabled participants to walk faster in the clinical setting.

Although there were no statistically significant group changes in community mobility, the sensor metrics highlighted *individual differences* in wear and usage of the novel device: some individuals showed a clear preference for wearing one KAFO over the other: 2 participants preferred wearing the novel device (4 and 14, **Wear Fraction** $=0.48$ and 0.57), while 3 participants favored their personal device (3, 9 and 13, **Wear Fraction** -0.52); the **Wear Fraction** for the remaining individuals was within -0.28 and 0.09 .

As before, we sought to understand whether these changes in clinical outcome measures or demographics were associated with changes in community mobility metrics; therefore, we computed the Pearson correlation coefficients between these differences, for each participant (Fig. 5).

Differences in 6MWT or 10mWT between the two devices were not correlated with changes in steps or cadence in the community (**6MWT- Steps:** $r=0.12$, $p=0.70$, **10mWT- Cadence:** $r=-0.05$, $p=0.87$), nor with changes in KAFO usage (**6MWT- Time Community:** $r=-0.08$, $p=0.81$; **6MWT- Wear Fraction:** $r=-0.20$, $p=0.51$). Therefore, higher walking speed or endurance measured in the clinical setting did not correlate with higher usage of the novel device in the community when compared to the personal device. Similarly, higher rating of the novel device versus the personal device, as measured by the OPUS score, was not associated with increased wear time (**OPUS- Wear Fraction:** $r=-0.18$, $p=0.55$), while it showed a significant negative correlation with changes in steps and cadence (**OPUS- Steps:** $r=-0.60$, $p=0.03$; **OPUS- Cadence:** $r=-0.73$, $p=0.005$).

Increased wear fraction showed a significant negative correlation with age (**Age- Wear Fraction:** $r=-0.62$, $p=0.023$), suggesting that younger users were more prone to use the novel device. The complete list of correlation values is provided in Table III (Supplementary Material). Overall, changes in clinical measures were not associated with individual changes of device usage and time in the community.

IV. Discussion

Tracking usage of assistive devices outside of the lab may provide insights into personal preferences, adaptation to novel devices, understanding appropriateness of device prescription, and justification for higher insurance reimbursement, all of which can aid clinical decision-making when an individual has to be prescribed a novel assistive device. We combined accelerometer and GPS data to quantify community mobility when participants used first their personal KAFO, and then a novel research KAFO. By combining information from the 2 sensors, we were not only able to record time spent at community locations, but also track how each assistive device was used in terms of steps taken and time worn. We then examined the association of these mobility metrics with standard clinical outcome measures to determine how well they reflected: 1) usage of their personal device and 2) changes in community mobility between the personal and novel KAFO.

We found that increased walking speed and distance measured in the clinic were correlated with higher steps and cadence in the community with the personal KAFO; however, mobility metrics varied widely between participants, and neither clinical tests nor self-reported measures (OPUS) were associated with usage of the KAFO or time spent at community locations. This suggests that real-world monitoring can provide additional information on how each individual use and wear a device. Interestingly, participants who walked slower in the clinic rated their personal device as more comfortable on the OPUS questionnaire; this could indicate that slower participants were also the ones who felt safer with their own device, and therefore perceived it as more comfortable. Alternatively, it is possible that faster walkers perceived their personal device as less adequate and therefore rated it lower.

Most participants used the novel KAFO as much as their personal device, as no overall changes in community mobility were found. This is remarkable, given that on average participants used a personal device for almost 30 years, and that they have only received six sessions of training/acclimatization on the novel KAFO. Usage of the novel KAFO in the community indicates that they were able to quickly adapt to the new technology and incorporated it as part of their daily routine. Some participants did however use the new device significantly more or less than their personal one: the 2 participants who preferred wearing the novel device are relatively young compared to the mean age of the group, while their years of experience using their personal device are widely different from each other (39 vs. 5 years). The 3 participants favoring their personal device also had different diagnoses and levels of experience from each other, but their age was greater than the group mean (≥ 65 years old). Long-term follow-up studies are required to better understand the variation we found.

Interestingly, improvements in clinical outcome measures (6MWT or 10mWT) and self-report measures (OPUS) with the novel KAFO did not correlate with increased usage or number of steps during community monitoring, relative to the personal device. For many physical rehabilitation populations, previous research suggests that clinical tests of speed and endurance can successfully differentiate individuals with different walking abilities [35]-[37]. However, such tests do not necessarily predict actual mobility in the community [22], [38], [39]. Similarly, self-report measures of mobility poorly correlate with activity quantified through step monitors [40]. While clinical measures appear to reasonably assess community mobility across individuals, our results suggest that subtler changes in mobility within an individual – such as when trialing a new device – may not be captured by changes in these same clinical measures.

Here, we did not evaluate the specific types of community destinations where the KAFO was used. The type of community destination may be associated with increased or decreased walking with KAFO. For instance, an individual may walk more at a grocery store than at a medical facility. Such analyses may in the future indicate whether a novel device provides greater advantages for specific destinations or activities, helping to prescribe devices suited to individual needs.

This monitoring strategy could be used to quantitatively compare the effect of different assistive devices on community mobility. While our sample was too small to draw a definitive conclusion on device preference and quality of life, and participants only used the novel device for 1 month, we were able to use wear times to detect differences in personal preferences in 5 out of 13 individuals (2 preferring the novel device and 3 preferring their personal device). Therefore, combining features from accelerometer and GPS data can be used to more directly answer important clinical questions and complement survey-based measures about the appropriate assistive device for an individual.

Here we used a GPS unit that participants wore on their waist to track their community mobility. Missing data partially occurred because participants occasionally forgot to wear and/or charge the device. Additional reminders and approaches to improve battery life may aid with better compliance [41]. Alternatively, smartphones and smartwatches are also capable of recording GPS location data with sufficient fidelity [42], [43] and could result in better compliance, as they are already part of the typical daily routine and don't require carrying a separate device. However, GPS-enabled smartphone applications can drain batteries and the accuracy varies by participant's phone model types. As technology progresses in this area, new devices or smartphone applications may help to improve overall compliance.

A. Study Limitations

The primary limitation of this study is the small sample size. With only 13 participants completing both the GPS and accelerometer tracking components of the study, it is difficult to fully analyze the differences in behavior while using the personal and novel KAFO devices. The small sample size also limits the potential generalizability of our results. While few participants showed strong device preferences there is insufficient data to fully evaluate the underlying factors that may relate to that: in our study, age was the only demographic

or clinical measure to show correlations with device preference, but there are many potential confounding factors, such as the underlying cause of impairment and previous exposure to the devices.

Because participants were only trained and monitored on the novel device for a relatively short time, participants may not have fully adapted to the new device and become experts, and our data may not reflect long-term differences in device preference. This may explain why we observed no significant difference in community mobility when participants used the novel device vs. the personal device. It is also possible that improvements in clinical measures are more correlated with device usage after participants have fully accommodated to the new device, which may take more time than the six sessions of training used in this study. Furthermore, participants monitored during the wintertime might have been affected by the weather conditions, and therefore used either device less for outdoor usage. All these factors would be accounted for by monitoring participants for longer periods of time. Finally, while studies have shown good agreement between the outputs of waist- and thigh-worn Actigraphs [44], more work is needed to explore its accuracy in individuals wearing a KAFO, which may require the need of custom step count and activity recognition algorithms [45], [46].

V. Conclusion

Long-term monitoring of patient behaviors relating to assistive device use and community mobility is possible by combining GPS and accelerometer sensor data. While this study focused on the application of these technologies to monitoring orthotic devices, the same technique can be applied to a much broader range of assistive devices, such as prostheses and wheelchairs. In particular, this approach could complement standard clinical outcome measures, and offer greater ability to quantify improvements in quality of life provided by new assistive devices, as well as personal preferences for using one device over another. With this additional insight, we may be able to better anticipate which patients will have better community mobility with different types of devices. With an increasing number of available technologies and a wide variety of individual patients, it is all the more important to understand how to match the best device to the individual. We hope that future studies will incorporate this method, in order to better understand the impact of mobility-assistive devices on the behaviors of those who use them and impact the design and prescription of future devices.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgment

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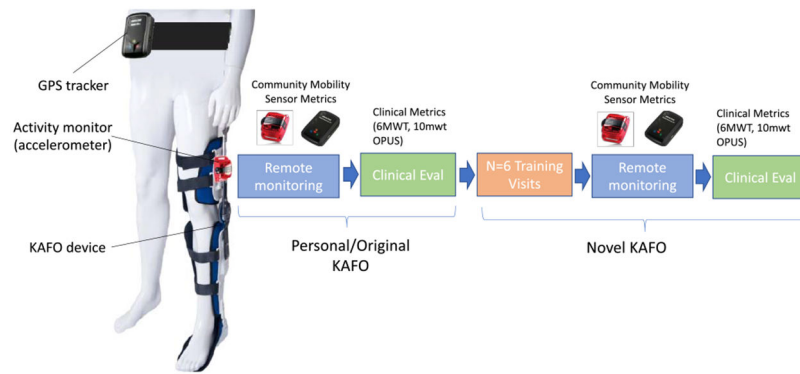


Fig. 1. (Left) experimental setup used to gather data on the usage of a knee ankle foot orthosis (KAFO). An activity monitor was attached to the participant's KAFO, to record when the assistive device was worn and the number of steps taken with it. A GPS was worn by the participant on the waist to track the geographical locations visited. (Right) Experimental protocol: sensors were used to gather KAFO usage data in the community over the course of 1 month (remote monitoring trial) with each KAFO device (personal and novel). At the end of each monitoring period, participants underwent a clinical evaluation. Six training sessions were also provided to participants to instruct them on how to use the novel KAFO.

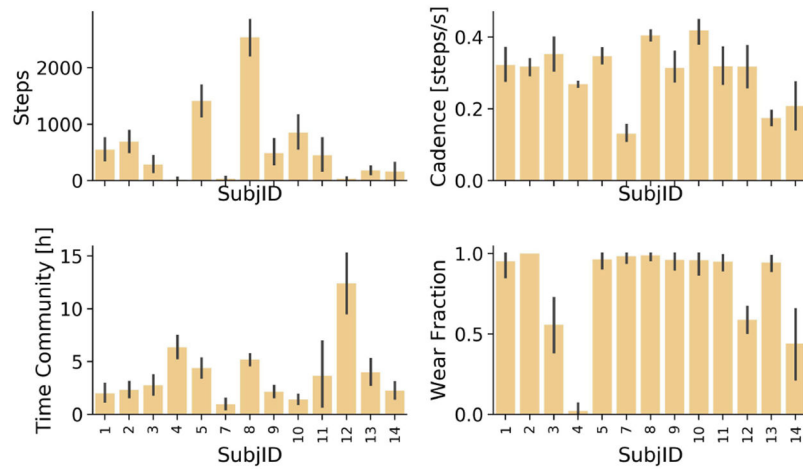


Fig. 2. Mobility metrics derived from GPS and accelerometer data for each participant. The derived metrics quantify usage of the personal KAFO in terms of steps, cadence, wear fraction as well as daily time spent in the community. Bars show mean daily values. Error bars are 95% confidence intervals of the mean.

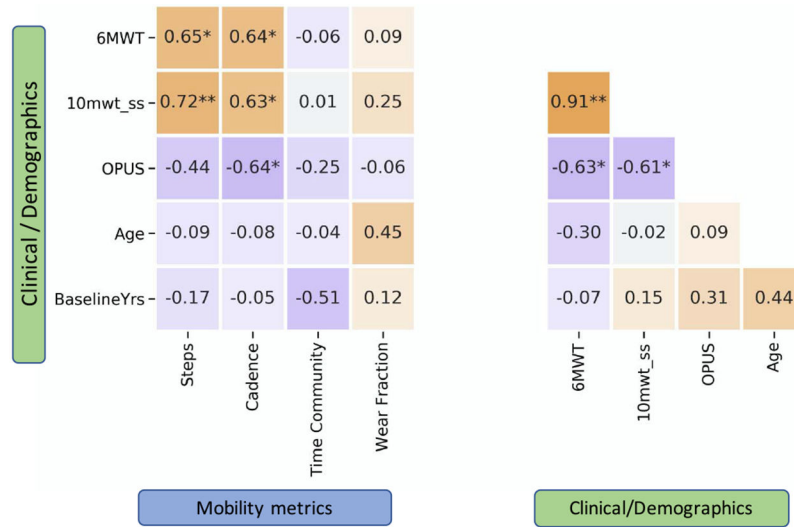


Fig. 3. Correlations of the 4 mobility metrics with clinical and demographics data for the personal KAFO. Clinical walking tests (6MWT and 10mWT) are correlated with steps and cadence in the community, but not with time wearing the KAFO (wear fraction) or time spent at community locations. Clinical tests of endurance (6MWT) and speed (10mWT) were highly correlated with each other. Darker colors indicate stronger correlations. (*: $p < .05$, **: $p < .01$).

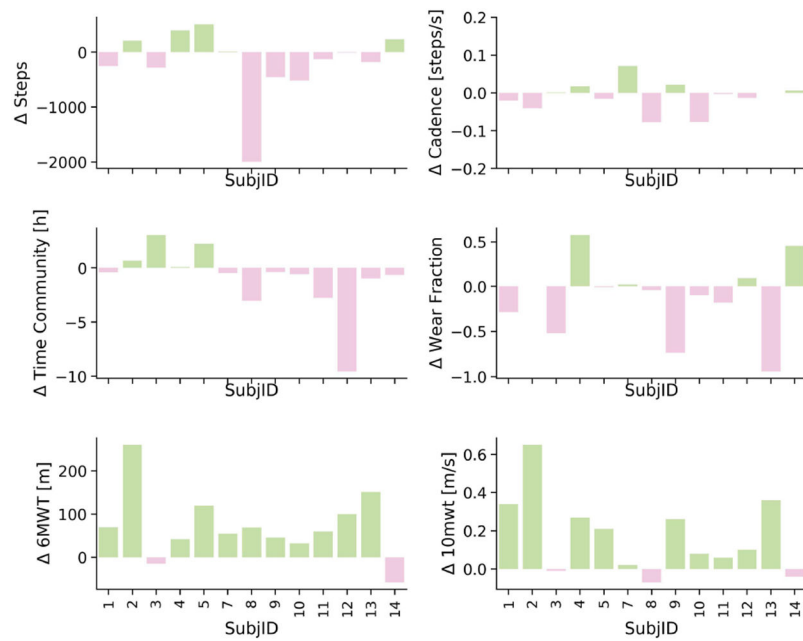


Fig. 4.

Differences () in mobility metrics and in clinical scores for each participant between the personal and novel KAFO. Positive values indicate higher usage/performance with the novel device. Green (red) indicates a metric increase (decrease) relative to the personal KAFO.

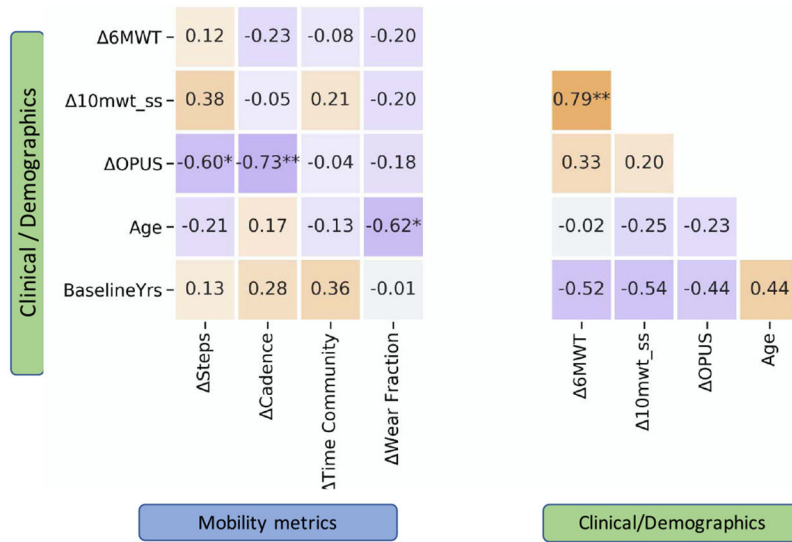


Fig. 5. Correlations of changes () in mobility metrics and clinical scores. Improvement in clinical scores (6MWT and 10mWT) were not associated with increased steps or usage of the device in the community. (*: $p < .05$, **: $p < .01$).

TABLE I

Participants Demographic Data

ID	Gender	Age at start of study	Years Using an Orthosis	Current Personal Orthosis (Baseline device)	Diagnosis
01	M	44	15	SCO	SCI
02	F	44	1	SCO	Neuropathy
03	F	65	60	Locked KAFO	Poliomyelitis
04	M	35	5	Locked KAFO	SCI
05	M	55	37	Locked KAFO	SCI
07	F	72	70	Locked KAFO	Poliomyelitis
08	M	52	0.5	Locked KAFO	TBI
09	M	68	30	Locked KAFO	SCI
10	F	68	66	Locked KAFO	Poliomyelitis
11	M	51	50	Locked KAFO	Poliomyelitis
12	M	65	40	SCO	Poliomyelitis
13	M	68	0.5	Locked KAFO	Encephalitis
14	F	41	39	Locked KAFO	Poliomyelitis

(SCI: spinal cord Injury; TBI: traumatic brain injury; KAFO: knee ankle foot orthosis; SCO: Stance control orthosis)