

## ORIGINAL ARTICLE

# Merging self-reported with technically sensed data for tracking mobility behavior in a naturalistic intervention study. Insights from the GISMO study

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Sound exposure data are central for any intervention study. In the case of utilitarian mobility, where studies cannot be conducted in controlled environments, exposure data are commonly self-reported. For short-term intervention studies, wearable devices with location sensors are increasingly employed. We aimed to combine self-reported and technically sensed mobility data, in order to provide more accurate and reliable exposure data for GISMO, a long-term intervention study. Through spatio-temporal data matching procedures, we are able to determine the amount of mobility for all modes at the best possible accuracy level. Self-reported data deviate  $\pm 10\%$  from the corrected reference. Derived modal split statistics prove high compliance to the respective recommendations for the control group (CG) and the two intervention groups (IG-PT, IG-C). About 73.7% of total mileage was travelled by car in CG. This share was 10.3% (IG-PT) and 9.7% (IG-C), respectively, in the intervention groups. Commuting distances were comparable in CG and IG, but annual mean travel times differ between  $\bar{x} = 8,458$  min ( $\sigma = 6,427$  min) for IG-PT,  $\bar{x} = 8,444$  min ( $\sigma = 5,961$  min) for IG-C, and  $\bar{x} = 5,223$  min ( $\sigma = 5,463$  min) for CG. Seasonal variabilities of modal split statistics were observable. However, in IG-PT and IG-C no shift toward the car occurred during winter months. Although no perfect single-method solution for acquiring exposure data in mobility-related, naturalistic intervention studies exists, we achieved substantially improved results by combining two data sources, based on spatio-temporal matching procedures.

## KEYWORDS

exposure data, GPS, intervention study, self-reported, travel diary, wearable devices

## 1 | INTRODUCTION

A key challenge in mobility-related intervention studies is the acquisition of sound exposure data, which is the distance travelled for each transport mode. Since studies that investigate everyday mobility cannot be conducted in a controlled environment, acquired data are always imperfect. Thus, the optimization of data quality in terms of completeness, accuracy, and reliability is a major concern. In practice, the trade-off between data demand for the respective study design and feasibility decides on the method for tracking people's mobility. In the past, mobility surveys and self-reported travel diaries have been the prime data source for long-term naturalistic intervention studies. Driven by technological advances over the past two decades, wearable sensors are increasingly employed for tracking purposes in mobility and health research.<sup>1</sup> However, there are no long-term intervention studies, which rely entirely on wearables yet. As it becomes evident from an overview of employed methods for data acquisition in recent observational and experimental studies (Table 1), long-term studies primarily use self-reported data. Wearables are commonly used for short-term investigations. In some studies, both methods are combined.

There is a wealth of studies that discuss the reliability and accuracy of self-reported mobility data in comparison to technically sensed data, which are commonly referred to as "objective data".<sup>2</sup> The latter include movement (accelerometer) and location (Global Navigation Satellite System, GNSS) sensors, as well as derived mobility data (eg, from mobile network operators). Kelly et al<sup>3</sup> explain the lack of quality of self-reported mobility data by "problems with adherence, memory and judgement" (p. 444). Consequently, data sets tend to be incomplete and contain wrong information about travel frequency and trip characteristics. On the other hand, self-reported data (retrospective questionnaire, travel diary etc) can be acquired from large samples over a long period with comparable little effort. Although technically sensed data are not prone to human biases, data acquisition with wearables does not lead to perfect results either. Correctly capturing all trips is impeded by handling errors and technical limitations. From 182 participants, equipped with GPS (Global Positioning System) devices for seven days, Panter et al<sup>4</sup> acquired 424 trips of which only 204 met the criteria for further analysis. Frehlich et al<sup>5</sup> compared questionnaire data with movement data (GPS and accelerometer) for a period of seven days. From 75 participants only 24 participants produced valid GPS and accelerometer data for the whole period. A similar study was conducted by Fillekes et al<sup>6</sup> with 27 subjects and an observation period of 30 days. From a total of 741 days, which were subject to analysis, self-reported and technically sensed data could be matched for 402 days.

Although huge progress in data acquisition has been made and data availability increased dramatically, there is no established framework for tracking subject's mobility in naturalistic intervention studies yet. In order to determine the health effect of workplace-related interventions for active commuting, accurate, long-term data about transport mode as well as trip distance and duration for every commute are needed. The aim of this sub-project of the GISMO (Geographical Information Support for Healthy Mobility) study is to increase the reliability and accuracy of self-reported mobility data by combining them with data from wearable devices, thus providing sound exposure data for a long-term intervention study.<sup>7</sup>

## 2 | MATERIAL AND METHODS

We used data from participants of the GISMO study. The rationales and design of the study as well as the recruiting procedure are described elsewhere.<sup>8</sup> In short, we included 73 subjects (aged  $46.0 \pm 8.9$  years at baseline, 26 males, 47 female) in the study, who commuted primarily by car and had the willingness to change to active commuting. Subjects were then randomized into an intervention and a control group. In the intervention group, subjects were further divided into two groups, mainly according to the respective commuting distance. Subjects in one group were requested to use primarily public transport in combination with walking or cycling for their commuting trips (IG-PT). The recommendation for the second group was to use the bicycle for commuting purposes (IG-C). Mobility data were acquired and analyzed for answering the following research questions at the level of individual subjects and for the intervention period of 1 year: (a) What is the amount of mobility, expressed in number of trips, total distance and travel time per mode? (b) Do subjects comply with the individual recommendations for behaviour change? (c) To which degree do seasonal variabilities in an alpine environment, as in Austria, influence subjects' mobility behaviour?

The GISMO study is registered at [clinicaltrials.gov](https://clinicaltrials.gov) under the identifier NCT03098719. Ethical approval was obtained from the Ethic Board of the University of Salzburg (EK-GZ: 43/2016).

### 2.1 | Data acquisition

We acquired data from two different data sources, namely travel diaries and fitness watches with location and heart rate sensors. For both data sources, pseudonyms were used in order to ensure anonymity for all subjects. The pseudonyms, together with the time stamp served as common key for the data sets (Figure 1).

**TABLE 1** Acquisition of exposure data in previous observational and experimental studies on health effects of active mobility

Study	Study design	Length of intervention/ observation	Sample size (recruited)	Method
de Geus et al <sup>10</sup>	Experimental: intervention	24 wk	n = 18	Travel diary + distance recorder
Prins et al <sup>11</sup>	Experimental: real-world intervention	2 × 7 d	n = 1582	Travel diary
Rosenkilde et al <sup>12</sup>	Experimental: randomized controlled trial	6 mo	n = 130 (PA measured for subgroup n = 51)	Smartphone
Fillekes et al <sup>6</sup>	Experimental: real-world intervention	30 d	n = 27	GPS tracker and accelerometer + travel diary
Costa et al <sup>13</sup>	Observational: cross-sectional	7 d	n = 550	Heart rate and movement sensor, GPS tracker + travel diary
Dons et al <sup>14</sup>	Observational: cross-sectional and longitudinal	290-694 d	Cross-sectional n = 7380 Longitudinal n = 2316	Online questionnaire
Hansen et al <sup>15</sup>	Observational: cross-sectional	7 d	n = 3479	ActiGraph accelerometer
Laeremans et al <sup>16</sup>	Observational: real-world monitoring	3 × 7 d	n = 122	SenseWear armband
Parra-Saldías et al <sup>17</sup>	Observational: retrospective, cross-sectional	1 y	n = 1288	Questionnaire



**FIGURE 1** Structure of sensed movement data (left) and travel diary (right) [Colour figure can be viewed at wileyonlinelibrary.com]

For the entire intervention period, subjects were required to document their commuting trips in a web-based travel diary. Commuting trips follow routines with little variation. In order to simplify the documentation of trips, participants were invited to store their set of routes and mode choices for every trip segment in the diary (variants). The respective variants were then selected and confirmed for every working day. Additionally, participants could add remarks to every diary entry. Trip frequency, distance, and duration for each mode were derived from the travel diaries.

In addition to the continuous documentation in the travel diary, we sampled two times two consecutive weeks at the beginning and toward the end of the intervention period for each subject. In these four weeks, subjects were asked to wear a fitness watch and record their commuting trips. For this purpose, we used off-the-shelf Polar® M200 fitness watches with an optical heart rate and location (GPS) sensor. Every subject received a personal introduction when he or she picked up the devices. All acquired data were stored on the device and transferred after return. We used a semi-automated method for data cleaning, travel mode

detection from GPS and heart rate data and determined the travel direction as proposed by Stutz, Westermeier.<sup>9</sup> In this approach, the data processing is automated, but manual interventions are necessary for visual inspection of intermediate results and calibrating the rule sets accordingly. In the data cleaning process, trajectories without or with fragmentary location information, below predefined thresholds for distance and travel time and without significant movement (stationary tracks) were removed. Additionally, segments with speed outliers were systematically filtered out and interpolated, respectively.<sup>9</sup> From the resulting data set, equaling in 1518 valid trajectories, relevant information on mode and route choice as well as on trip frequency, distance, and duration was extracted.

Weather data were acquired from the national meteorology service (ZAMG) for the measuring station closest to the participants' workplace. Between May 2017 and June 2018, the minimum temperature was  $-17.0^{\circ}\text{C}$ , the maximum  $36.0^{\circ}\text{C}$ . The total precipitation recorded for this period was 1871.9 mm.

## 2.2 | Data matching and statistics

Travel diary entries and data from the fitness watches were matched based on their time stamp and travel direction. The workflow of the data matching consists of two major steps (Figure 2). First, processed and segmented trajectories<sup>9</sup> for each subject are matched to travel diaries on the basis of a common time stamp and identical travel directions. Second, variants in the travel diary are corrected by the processed and validated trajectory data. This results in corrected exposure data for each subject and transport mode.

The quality of acquired exposure data is fundamental for any conclusion drawn from experimental studies. However, data from mobility tracking in a naturalistic environment are flawed, irrespective of the data source. In order to account for this, we attached information on the quality of tracking data in terms of reliability and accuracy. For the present case, where data from travel diaries are merged with sensor data, we propose an assessment of the matched data that is built upon two distinct elements. First, we consider the number of entries in travel diaries. The maximum number of working days and thus, the maximum number of possible entries to the travel diary, is used as basis (depending on which days holidays fall, there are approximately 250 working days per year in Austria). We rate travel diaries with  $>80\%$  of possible entries as very good,  $>60\%$  as good,  $>40\%$  as moderate, and below as bad. Second, the quality of tracking data is assessed in terms of quantity, signal quality (signal deviation and loss or cold start), representativeness of trip routines (trajectories may deviate from the majority of data because of singularities), and contribution to explaining travel diary entries (trajectories may be of good signal quality but do not correspond

with any documented trip). For the total of 4 weeks of data acquisition, we rate  $>15$  suitable trajectories as very good,  $>10$  as good,  $>5$  as moderate, and less as bad. The overall assessment of the combined mobility record of each subject is calculated as the mean of the two rankings.

All data were stored in a PostgreSQL 9.5 database, where we also calculated statistics. For spatial analyses, the spatial extension PostGIS 2.3.7 was employed. Tableau 2018 and QGIS 3.4 were used for visualization purposes. Statistics were calculated for all subjects with at least one travel diary entry, regardless of any dropout.

## 3 | RESULTS

In total, we acquired 10 566 travel diary entries from 66 participants and 1509 trajectories from 60 participants, with a mean number of 160 entries per person ( $\sigma = 93.43$ ). The corrected amount of mobility for all considered subjects, regardless if their data were used for any other analysis in the GISMO study, is summarized in Table 2.

### 3.1 | Increasing accuracy of exposure data

For the two periods of two weeks each, in which subjects were required to track their mobility by fitness watches, we can compare exposure data for the two considered data sources. Table 3 summarizes the acquired data for the control and the two subgroups of the intervention groups for these 4 weeks. For the calculation of the total travel distance and time, uncorrected, but synchronized data from both sources were considered. It becomes obvious that the deviation from the corrected reference data is comparable small for entire groups, due to leveling out effects. In contrast, the variance is high at the level of individual subjects, especially in data from travel diaries. Data from CG suggest an underestimation of travel distance and time, with substantial differences between the two considered data sources. For IG-PT, the total travel distance is underestimated and total travel time overestimated. Data from IG-C show an overestimation of travel distance and time from all data sources.

The deviation of values can be explained by the primarily used transport modes in the respective group. Figure 3 indicates the over- and underestimation of travel diary data compared with corrected reference data.

Walking distances tend to be overestimated, whereas the travel distance for all other modes are closely scattered around the median values, which correspond with the corrected reference data. Travel times are accurately documented in travel diaries for car trips, but overestimated for all other modes. The interquartile ranges (IQR) are larger for walking and public transport trips than for commutes done by bike and car, respectively.

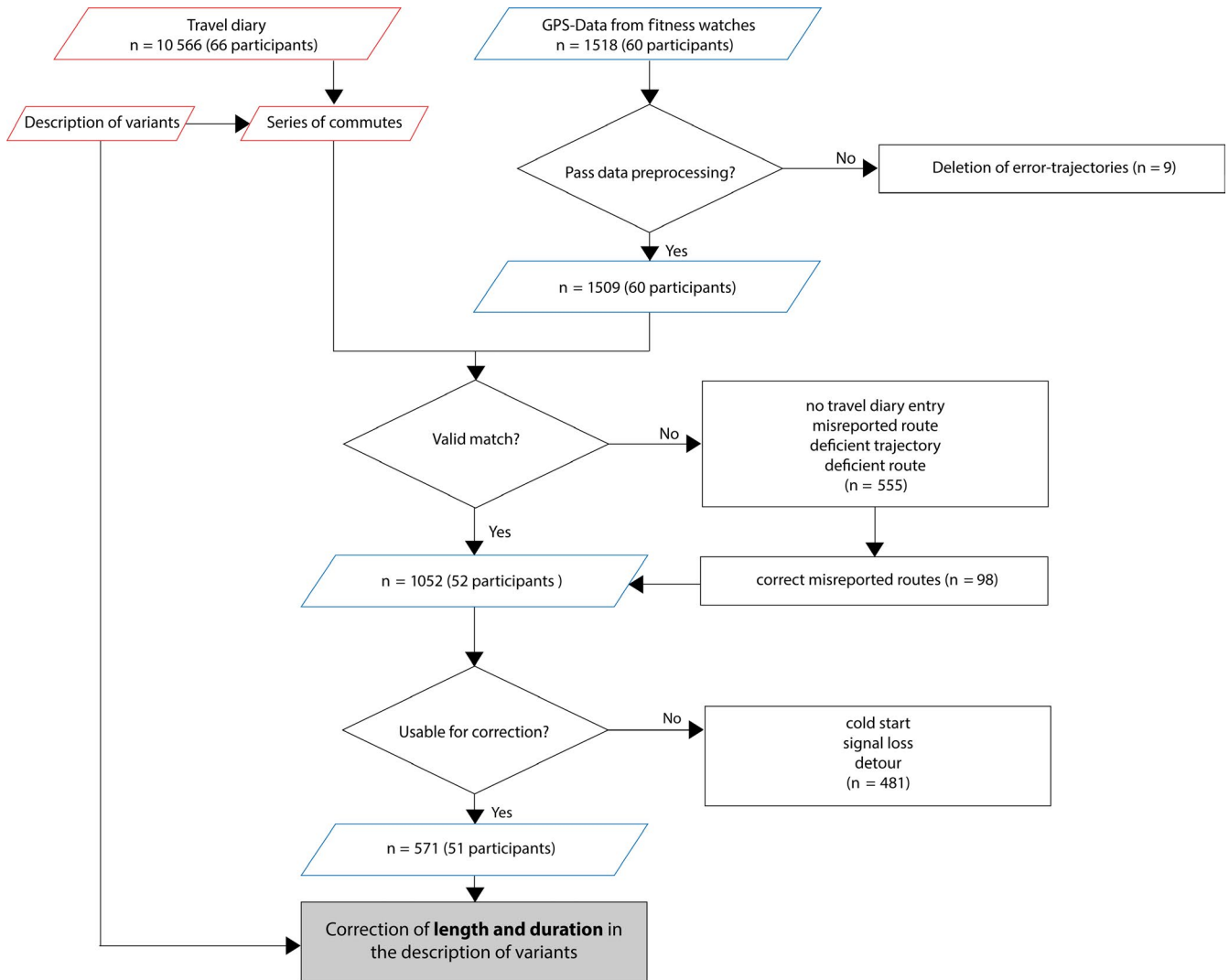


FIGURE 2 Workflow for matching data from travel diaries and fitness watches [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 2 Total amount of mobility for all groups and transport modes

Group	Total distance (km) travelled				Total time (min) travelled			
	Walk	Bike	PT	Car	Walk	Bike	PT	Car
CG (N = 19)	1948	1056	11 361	40 300	22 027	4723	17 318	49 874
Per subject	$\bar{x}$ = 103 $\sigma$ = 160	$\bar{x}$ = 56 $\sigma$ = 111	$\bar{x}$ = 598 $\sigma$ = 1549	$\bar{x}$ = 2121 $\sigma$ = 4081	$\bar{x}$ = 1159 $\sigma$ = 1827	$\bar{x}$ = 249 $\sigma$ = 522	$\bar{x}$ = 911 $\sigma$ = 2368	$\bar{x}$ = 2625 $\sigma$ = 4174
IG-PT (N = 24)	7021	10 400	42 807	6895	76 466	35 626	71 125	11 239
Per subject	$\bar{x}$ = 293 $\sigma$ = 236	$\bar{x}$ = 433 $\sigma$ = 587	$\bar{x}$ = 1784 $\sigma$ = 3303	$\bar{x}$ = 287 $\sigma$ = 497	$\bar{x}$ = 3186 $\sigma$ = 2813	$\bar{x}$ = 1484 $\sigma$ = 1977	$\bar{x}$ = 2964 $\sigma$ = 3941	$\bar{x}$ = 468 $\sigma$ = 848
IG-C (N = 23)	1486	38 253	27 552	7242	19 105	122 966	32 930	10 654
Per subject	$\bar{x}$ = 65 $\sigma$ = 116	$\bar{x}$ = 1663 $\sigma$ = 1109	$\bar{x}$ = 1198 $\sigma$ = 3012	$\bar{x}$ = 315 $\sigma$ = 634	$\bar{x}$ = 831 $\sigma$ = 1797	$\bar{x}$ = 5346 $\sigma$ = 2913	$\bar{x}$ = 1432 $\sigma$ = 4326	$\bar{x}$ = 463 $\sigma$ = 804

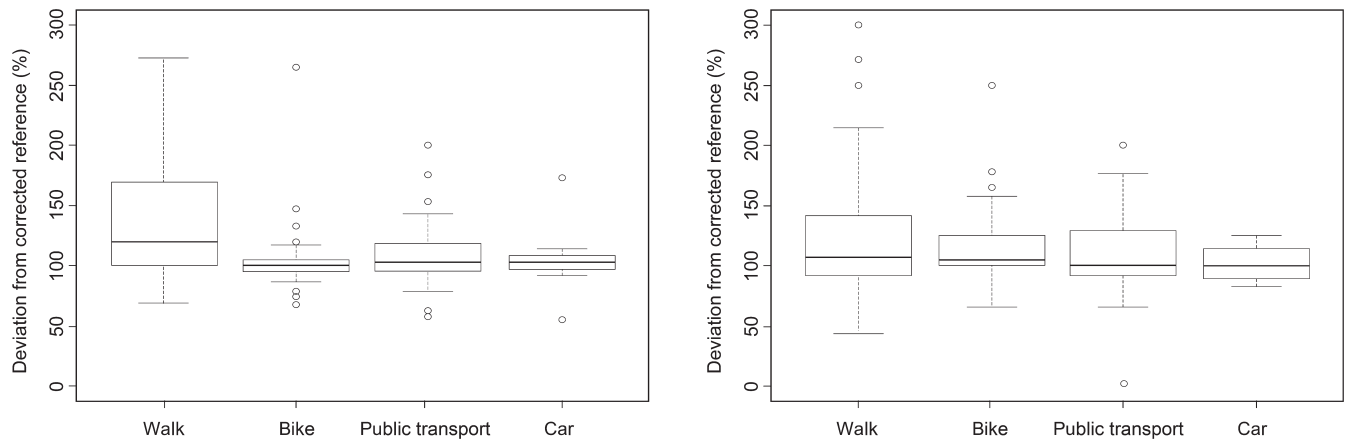
The quality of the acquired data differs substantially. Considering the combined quality of travel diary and trajectory data, the resulting exposure data of 30 subjects (45%) are rated as very good, of 6 (9%) as good, of 10

(15%) as moderate, and of 20 (30%) as bad. The mean number of travel diary records is 160.10 ( $\sigma$  = 93.43,  $\bar{x}$  = 177.5) and the mean number of recorded trajectories is 25.52 ( $\sigma$  = 12.45,  $\bar{x}$  = 25).



**TABLE 3** Comparison of raw data from two data sources with corrected reference. Only days where travel diary entries and trajectories are available are considered. Mean travel distance and time are calculated per day

Group	Total distance (km) travelled			Total time (min) travelled		
	Source: travel diary	Source: fitness watch	Matched and corrected	Source: travel diary	Source: fitness watch	Matched and corrected
CG (N = 12) 177 d	2295 99.35%	2184 94.55%	2310 100%	4368 99.09%	4909 111.37%	4408 100.00%
Per day	$\bar{x} = 13.0$ $\sigma = 13.0$	$\bar{x} = 12.3$ $\sigma = 12.8$	$\bar{x} = 13.1$ $\sigma = 13.1$	$\bar{x} = 24.7$ $\sigma = 17.4$	$\bar{x} = 27.7$ $\sigma = 21.2$	$\bar{x} = 24.9$ $\sigma = 17.6$
IG-PT (N = 20) 471 d	5680 105.54%	4807 89.32%	5382 100.00%	16 725 108.90%	15 522 101.07%	15 358 100.00%
Per day	$\bar{x} = 12.1$ $\sigma = 13.4$	$\bar{x} = 10.2$ $\sigma = 13.5$	$\bar{x} = 11.4$ $\sigma = 13.5$	$\bar{x} = 35.5$ $\sigma = 22.9$	$\bar{x} = 33.0$ $\sigma = 25.9$	$\bar{x} = 32.6$ $\sigma = 23.5$
IG-C (N = 20) 450 d	5837 100.38%	5744 98.78%	5815 100.00%	13 269 101.10%	15 560 118.55%	13 125 100.00%
Per day	$\bar{x} = 13.0$ $\sigma = 14.2$	$\bar{x} = 12.8$ $\sigma = 15.3$	$\bar{x} = 12.3$ $\sigma = 14.9$	$\bar{x} = 29.5$ $\sigma = 19.5$	$\bar{x} = 34.6$ $\sigma = 30.2$	$\bar{x} = 29.2$ $\sigma = 21.4$



**FIGURE 3** Deviation of travel distance (left) and time (right) in travel diary data from corrected reference for all transport modes

**TABLE 4** Compliance with recommended transport mode: modal split based on mileage and travel time for each group

Group	% travel distance per group and mode				% travel time per group and mode			
	Walk	Bike	PT	Car	Walk	Bike	PT	Car
CG (N = 19)	3.6	1.9	20.8	73.7	23.4	5.0	18.4	53.1
IG-PT (N = 24)	10.5	15.5	63.8	10.3	39.3	18.3	36.6	5.8
IG-C (N = 23)	2.0	51.3	37.0	9.7	10.3	66.2	17.7	5.7

### 3.2 | Compliance with recommendations

Each group was instructed to primarily use specific modes of transports. Subjects in CG should continue using their car for commuting purposes. Biking was the recommended mode for IG-C and public transport in combination with walking for IG-PT. All participants were introduced in workshops and provided with incentives.<sup>8</sup> The corrected mobility data show

an overall high compliance with the respective recommendations (Table 4).

Whereas the car remained the primary transport mode (73.7% of mileage) for CG, subjects in IG-PT and IG dramatically reduced their car trips with a relative mileage of 10.3% (IG-PT) and 9.7% (IG-C), respectively. For the intervention period of one year, the mean travel time for IG-PT ( $\bar{x} = 8458$  min,  $\sigma = 6427$  min) and IG-C

( $\bar{x}$  = 8444 min,  $\sigma$  = 5961 min) was higher than for CG ( $\bar{x}$  = 5,223 min,  $\sigma$  = 5463 min). Relating travel times with the distance travelled, IG-PT (20.71 km/h) turns out to be the slowest group compared to IG-C (24.10 km/h) and CG (34.90 km/h).

### 3.3 | Sensitivity to seasons

Because pedestrians and cyclists are directly exposed to weather conditions, the variation of mobility behavior over the intervention period is of great interest. Therefore, the corrected mobility record was segmented into seasons. The calculated modal split based on mileage is summarized in Table 5.

The car is the preferred mode of transport for CG throughout the year. A majority of subjects in IG-PT used public transport in combination with walking during winter. Cycling is marginal in winter, but accounts for 24.7% of the total distance travelled in summer. Seasonal effects become evident in IG-C with a clear shift from bicycle trips to public transport during the winter season. During summer, 55.8% of mileage is done by bicycle. Overall, the car accounts for a maximum of 14.3% of the total distance travelled in both intervention groups. Seasonal effects are observable in IG-PT and IG-C, but no shifts toward the car, which had been the preferred mode for commuting initially, could be observed.

## 4 | DISCUSSION

The share of active mobility was substantially higher in IG-PT and IG-C compared with CG. Promoting the usage of public transport for commuting purposes, automatically increases walking and cycling. Interventions toward cycling

result in remarkable cycling volumes and increases the distance travelled by public transport.

### 4.1 | Increasing accuracy of exposure data

Comparing mobility data from travel diaries and fitness watches reveals patterns of over- and underestimating distance and travel time. Highest deviations from measured trip characteristics occur in self-reported data on walking trips. Travel times for public transport trips are overestimated in travel diaries.

Self-reported data deviate approximately  $\pm 10\%$  from the corrected reference. Deviations from uncorrected trajectory data are even more substantial. Travel times are overestimated due to handling errors in conjunction with technical limitations of the used fitness watches. The GPS sensor of the employed Polar® M200 took some seconds for receiving the signals and failed to do so when subjects already moved (cold start). Consequently, recorded trajectories are geometrically shorter (no GPS point) than the time stamp would imply. These findings are of high relevance with regard to the attribution of technically sensed as “objective” data. The amount of useable trajectory data (571 from 1518) for the matching with self-reported travel diary data is comparable to similar studies.<sup>4,6</sup>

Overall, the combined and corrected exposure data are more accurate than each of the data sources would be on their own. It became obvious that subjects who documented their commuting mobility well in their travel diaries also recorded enough useable trajectory data and vice versa. Consequently, the accuracy and reliability of exposure data acquired in a naturalistic setting do not only depend on the acquisition technique, but also on the commitment of subjects. However, the combination of self-reported and technically sensed data facilitates data correction routines, which result in an overall higher quality of exposure data.

Group	Season	Walk %	Bike %	PT %	Car %	
CG (N = 19)	Winter	4.8	1.4	11.5	82.3	100%
	Spring	4.3	8.6	22.2	65.0	100%
	Summer	2.9	6.7	23.9	66.5	100%
	Autumn	2.5	5.3	23.0	69.2	100%
IG-PT (N = 24)	Winter	13.2	1.7	72.3	12.7	100%
	Spring	10.5	16.8	65.5	7.2	100%
	Summer	8.5	24.7	55.0	11.8	100%
	Autumn	10.4	15.1	65.1	9.5	100%
IG-C (N = 23)	Winter	4.5	40.6	41.8	13.1	100%
	Spring	2.2	50.7	39.2	7.8	100%
	Summer	0.7	55.8	29.2	14.3	100%
	Autumn	1.4	48.7	41.9	8.0	100%

**TABLE 5** Modal split based on mileage for each season

## 4.2 | Compliance with recommendations and sensitivity to external factors

The acquired mobility data suggest a high compliance with mobility recommendations for all groups. The highest share of total mileage was recorded for the car (CG), public transport (IG-PT), and the cycling (IG-C), respectively. Thus, it can be concluded that a switch from car commuting to active modes was induced by the employed promotion activities and provided incentives. Subjects show little sensitivity to weather conditions. If any, subjects switched to sustainable modes during the winter season instead of switching back to the car.

## 4.3 | Applicability in long-term intervention studies

Movement data acquisition and handling, which goes beyond self-reported approaches, requires substantial effort and specific skills. This adds to the overall high effort of long-term interventions studies with a large enough sample size.

Regardless of the effort, the combination of self-reported and technically sensed data proved to be applicable. We showed that travel diaries are well suited to document commuting frequencies. Movement data from wearable devices are far from being complete, due to handling and measurement errors. Still, if they are corrected for these errors, exact data on transport mode choice, travel distance, and duration can be delivered.

We therefore argue for a combination of data acquisition techniques in order to get the best possible exposure data. The presented approach extends and bridges common practices for longitudinal and long-term intervention studies (self-reported) on the one hand, and for more limited settings (wearable devices) on the other.

## 4.4 | Limitations

The focus of this study is primarily on the quantification of commuting mobility of individual study participants. Consequently, general conclusions on mode choice or the amount of active mobility cannot be drawn from this sample. For this, substantially larger samples are required.

The proposed approach is laborious and requires advanced skills in massive, spatial data handling. Moreover, the quality of acquired data is limited. Optimizing interfaces for self-reporting and improving the handling of wearable devices is essential. However, as long as subjects of intervention studies need to be equipped with specific

sensors, the sample size is limited by the required effort. Passive sensing techniques (eg, data from cell phone operators or smartphone tracking apps) would allow for larger samples but raise additional issues in terms of data validity and privacy.

Although much effort was invested to constantly remind subjects to fill in their travel diaries, we cannot guarantee full coverage. Vacations, sick leaves and irregular shifts could not be fully captured. Cross-checking travel diaries with time records were not possible due to legal reasons. However, time record systems, where employees are prompted to document their commuting mode are already on the market.

## 5 | PERSPECTIVE

This study adds to previous work, which point to the limited accuracy of self-reported mobility data. We demonstrated systematic overestimations in self-reported data, especially with regard to travel time for walking and public transport. Although, wearable devices could be employed for deriving corrected exposure data, we do not agree with an exaggerated positivism toward technical solutions. From the total of collected trajectories, only 38% were suitable for correcting self-reported data. We therefore conclude that no perfect single-method solution exists for acquiring exposure data in mobility-related, naturalistic intervention studies. Hence, by converging two data sets according to the temporal and spatial matching procedure described here, the validity of exposure data can be substantially improved.

Given the fact that far-reaching conclusions are derived from intervention studies, we regard any investment in sound exposure data as worthwhile. With regard to commonly available technical skills for acquiring, handling, and analyzing massive movement data in medical research, we call for cross-domain collaborations as exemplified in the present GISMO study. The increasing availability of movement and fitness data, largely driven by the so called quantified-self movement, and the advancing digitalization in medicine (“digital health”), will open whole new research opportunities. The present study is regarded as a first step toward this direction.

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