USING A GPS ACTIVE LOGGER TO IMPLEMENT TRAVEL BEHAVIOR CHANGE PROGRAMS

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ABSTRACT

Implementing behavioural strategies aimed at reducing car use represents one of the most topical challenges for current transport research.
Most of the current voluntary travel behaviour change (VTBC) programs are moving towards ICT devices for data collection. The advantages of using ICT have been recognized for implementing behavioural strategies and VTBC, in order to improve observation of pre- and post-implementation behaviour.
This paper describes the implications of a personal active logger (AL) implemented by CRiMM (University of Cagliari, Italy) for the collection of individual activity-travel patterns before and after a VTBC implementation. In particular, VTBC data collected through an active tracking system (GPS tracking + real time activity diary completion) are compared with data collected using a hybrid tracking system (GPS-only system + deferred activity-travel patterns). The results show that, despite the greater effort involved in real time compilation, the information collected by the active logger is more in line with VTBC requirements and expectations.
Keywords: Data collection, GPS active logger, Soft measure

1. INTRODUCTION

Implementing behavioural strategies, aimed at reducing individuals' need to drive, represents one of the most topical challenges for current transport research (Handy and Krizek, 2009). For this purpose, a number of Voluntary Travel Behaviour Change programs (VTBC) have been implemented in different countries, including Australia, UK, Japan, Germany, and Austria (Ritcher *et al.*, 2011).
So far, VTCB policies have resulted in a 5 to 15% reduction in kilometres travelled (Brög *et al*., 2009), but in order to also facilitate the shift towards sustainable modes some aspects of the VTBC still need particular attention (Stopher *et al*., 2009). Travel behaviour is increasingly linked to individual daily activities. It is therefore crucial to acquire methods and

tools for data collection that are able to detect the entire sequence of daily activities and trips. In particular, spatial and temporal attributes as well as quantitative behavioural aspects (activity times, waiting times, chosen routes, *etc*.) need to be incorporated into data collection.
Among others, Stopher (2005) identifies three main guidelines to improve VTBC programs, all related to the reliability of the available data. First, activity-travel patterns must be measured before each policy implementation, so that personalized travel plans can be designed for each participant according to his/her specific needs; second, activity-travel patterns should preferably be measured also after policy implementation, in order to establish whether a change has occurred and its effects on personal activity-travel patterns; third, the high variability involved in daily activity-travel patterns - and especially in the context of soft measures - needs to be captured, collecting data for repeated observations (Stopher, 2005).

From these guidelines, some behavioural aspects emerge that are important for collecting data to be used for VTBC implementation. The first concerns the personalization of measures: by collecting activity patterns it is possible to devise personalized solutions. The personalized quantitative feedback is in fact utilized to describe the benefits on a personal level associated with the proposed solution, acting as a lever for behaviour change. Additionally, personalized measures make participants more responsible as to the importance of their contribution (active support). Moreover, monitoring post-implementation behaviour, besides being valuable for evaluating the effectiveness of the VTBC measure, also strengthens the measure itself, encouraging participants to continue their commitment.

In this context, the availability of new technologies (GPS, Internet, Smart phones) has made it possible to collect repeated data, of higher quality and at lower costs (Meloni *et al.*, 2011), and GPS data have been conveniently employed in Mobility Management and behavioural strategies in general (Brög *et al*., 2009; Socialdata Australia, 2006a; 2007a). Generally speaking, the use of GPS technology came about through a passive tracking system that requires a post processing phase implemented on well defined GIS to reconstruct activity-travel patterns. The most recent active loggers, smartphones or PADs with dedicated applications, enable users to record their activities and trips in real time together with the relative attributes. Another type of data collection, the so-called Hybrid, consists of a passive system combined with the compilation of a classical activity-travel diary a posterior (Schönfelder *et al.*, 2002).

Though there exists general consensus that the use of GPS technologies can have positive effects on the implementation quality and evaluation of VTBC programs compared to the traditional survey methods (reduced burden on participants, tracking active travel and public transport), in spite of the technological hitches that may rise (GPS signal not found, battery life, *etc*.) (Stopher *et al.,* 2009), the implications of using an active rather than a hybrid system are still not clear.

The present work contributes to the state of art by providing a comparison of active vs. hybrid methods and their implications on VTBC implementation. Specifically, the aim of this work is to compare the accuracy of the two methods in collecting daily activity-travel patterns for the creation of personal travel plans (PTP). The active logger employed in this study is a smartphone with incorporated software application that combines GPS data with real time activity-travel attributes (Meloni et *al.*, 2011). The hybrid alternative has been created asking participants to use the same device in GPS-only mode, accompanied by a telephone interview (activity-travel data) at the end of the day. The active logger offers a number of advantages namely (1) comprehensive collection of daily activity-travel patterns and related attributes, (2) GPS tracking of daily routes and (3) evaluation of transport policy effects aimed at promoting sustainable mobility (before and after studies). On the other hand, the hybrid GPS-only system demands less effort on the part of the participants during the survey day and is more suited to frenetic daily schedules.

The rest of the paper is organized as follows. The next section briefly describes the existing voluntary travel behaviour change approaches and data collection methods adopted. Section 3 describes the methodology employed in this work in terms of overall strategy design, data collection and used device. Section 4 analyzes the results of the study and finally, section 5 contains the conclusions and further research opportunities.

2. LITERATURE REVIEW

Soft measures are policy interventions aimed at interfering directly in individual decision making processes to promote voluntary behavioural changes (Bamberg *et al.*, 2011). As opposed to “hard measures” that attempt to modify people’s travel choices as an indirect effect of taxes and fees (*i.e.* road pricing, parking fees, *etc*.), soft measures lead people to reconsider their mobility styles, encouraging them to strike a balance between different modes of transport (Bamberg *et al.*, 2011). The basic concept is that information and awareness raising about the effects of car use on personal and societal well-being is essential for promoting travel behaviour change.

Under various names and forms soft measures - also referred as Voluntary Travel Behaviour Change programs (VTBC) - have been implemented mainly at a personal and community level (mass communication), in different countries, especially in Australia, UK, Japan, Germany, and Austria among others (Ritcher *et al.*, 2011). Although the number of marketing campaigns aimed at motivating communities to embark on sustainable behaviour is increasing constantly (*i.e.* recycling, energy saving, green products, active trips campaigns, *etc*.), personalized communication seems to be more effective than social marketing (Fujii and Taniguchi, 2006) especially for travel behaviour change.

In particular, motivational drivers are most likely to differ from one person to another (*i.e.* economic, environmental and societal drivers) (Ampt, 2003) and car use is closely interwoven with individual daily activity-travel patterns (Steg and Tertoolen, 1999).

Programs that use personalized information and communication are defined as Personalized Travel Planning (PTP). They aim to provide individuals with travel-related information based specifically on their daily activity-travel needs. Some examples of PTP are Travel Feedback Programs (Fujii and Taniguchi, 2006), IndiMark and Travelsmart (Brög *et al.*, 2009), and Travel Blending (Ampt, 2003). In particular all these programs differ mainly for (1) the level of policy personalization (*i.e.* info related to alternative travel modes vs. activity-travel plans), and for (2) the type of suggestions (improving balance between travel modes vs. car use reduction only). These differences are strongly related to the type of activity-travel data collection adopted.

Most of the programs, in fact, do not observe current travel behaviour, but they provide each individual with general tips about existing alternatives (Indimark). However, there is another branch of VTBC programs that design the methodological approach (creation of PTP) and program evaluation through observation of existing behaviour before and after program implementation (Travel Blending and TFPs for instance). In these programs behaviour is determined on the basis of patterns recorded in activity-travel diaries, completed over several days. In some cases the diaries can be accompanied by the use of an odometer, in order to measure the distances travelled by car.

Some authors have shown that these methods (diaries + odometer) may not be appropriate for a behavioural strategy, especially for evaluating the measure. In fact, these methods only provide details about changes in vehicle kilometres travelled and do not allow to assess shifts to public transport, walking and cycling, (Stopher *et al.*, 2009). On the other hand, research on travel surveys has shown a number of issues that characterize the quality of data recorded using activity-travel diaries. These issues are related to non-response, human error, trip omission and drop-out, all of which can be partially attributed to burden of participation. The compilation of diaries at the end of the day creates problems because human memory is often less than perfect (Titheridge and Simpson, 2011). It has been shown that problems of human recall affect short trips or chained trips in particular, and are easily omitted by participants (Wolf *et al.*, 2003, Wolf, 2006; Stopher *et al.*, 2007), especially when the survey is carried out over several days (Du and Hall, 2007).

In this regard, GPS technologies have been recommended (Stopher *et al.,* 2005) as a potentially valuable tool for fulfilling these requirements. Over the past decade, GPS technology has been increasingly used in travel behaviour research to assess and evaluate the accuracy of travel data reported in diaries. Through such evaluations, and assuming that GPS data provides “true” measures of trip-making, it has been documented that household travel survey data, by virtue of their reliance on self-reported information by respondents, suffer from incompleteness and inaccuracies of reported trips. As a result, the under-reporting of trips is seen as a major drawback of household travel surveys (Bricka *et al.,* 2012).

GPS survey methods have been shown to substantially reduce human error. For example, work by the UK Department for Transport (2009) found that travel diaries in the National Travel Survey (NTS) captured a lower number of walking trips under one mile in length, compared to when participants were measured simultaneously by GPS methods. GPS’s primary advantage is the rich spatial and temporal data one is able to capture whilst its passive measurement nature reduces participant burden as all that is required is for the device to remain charged and to be carried (Bricka & Bath 2006). Despite these advantages, there are a number of problems including processing errors, technical equipment errors and human error.

In general GPS technology is used in three different ways in activity-travel surveys: (1) passive tracking, (2) hybrid tracking and (3) active tracking (Schönfelder *et al.*, 2002). Passive GPS devices require no inputs by the survey respondent during use (Stopher *et al.*,

2009), meaning that users are required simply to carry the device with them (Stopher, 2009). Data collection tracks the paths covered by each user and the related information (such as trip origin and destination end of the trip, trip purpose, duration of activity at destination, *etc*.) is gleaned using advanced post-processing algorithms performed on GIS platform (Stopher *et al*., 2005; Tsui and Shalaby, 2006; Stopher *et al*., 2007; Schönfelder and Axhausen, 2005, Wolf *et al*., 2001).
An alternative to completely passive data collection with post-processing is to use passive data collection with some type of follow-up survey. This is usually referred to as hybrid and can include prompted-recall survey by a telephone or web-based.
Most discussions regarding the application of new technologies in travel surveys focus on the development of interactive devices, in which case the user is expected to enter data that will be recorded along with position records (Stopher 2009). This system is referred as GPS active logger and consists of a smartphone with apps to replace the paper travel diaries (Bricka and Murakami, 2012). Active GPS tracking permits activity-travel data collection in real time. A smartphone with specific applications records spatial information via GPS, and integrates these data with activity-travel data provided in real time by the user (travel mode, company, purpose, parking fees/ticket fare, *etc*.).
The advantages of using GPS technology have been recognized for implementing behavioural strategies and VTBC, in order to improve observation of pre- and post-implementation behaviour (Brög et al 2009; Stopher, 2009; Taylor, 2007; Richter *et al.*, 2011). Some authors report experiences with VTBC surveys using GPS-Based survey to collect data (Stopher *et al.*, 2007), also supplemented by diaries (hybrid system) (Ampt *et al.*, 2006).
Stopher *et al.* (2009) conducted a comparative study of passive GPS logger and odometer surveys as part of the TravelSmart Households in the West project undertaken in South Australia. Results showed higher quality in data collection (number of trips detected and distance travelled), although they experienced problems related to behavioural change detection (increased walking, cycling, use of public transport*)*.

3. METHODOLOGY

The VTBC program implemented by CRiMM (Research Center in Mobility Models), University of Cagliari (Sardinia, Italy), began in February 2011 and ended in June 2012 (18 months). The program was designed as an experimental analysis of methods and techniques whose ultimate objective was to develop a behavioural model of travel behaviour change. In particular, in 9 different waves, 109 car users in the Cagliari Metropolitan area were invited to record their activity-travel patterns before and after the submission of personalized travel plans (PTP). More specifically, the PTP contained individually tailored information on how to incorporate an existing light rail service into their daily activity-trips. The necessary individual data was collect during one-week activity-travel pattern survey. After PTP submission, the one-week activity-travel diaries were collected to identify possible travel behaviour changes. The entire data collection phase was supervised by mobility advisors.

Importantly, observing the activity-travel patterns before implementation of the soft measure allowed us to identify a wide range of personalised sustainable alternatives, in terms of

modal shift and spatial and temporal distribution of activities. In particular, all data collected in the pre-implementation phase were used to prepare a PTP for each participant. The data were also spatially analysed using GIS and a transport simulation model calibrated for the network of Cagliari (Cube by Citilabs), in order to design the alternatives to be proposed in the personalized travel plan (for a review of PTP design see Meloni *et al.,* 2012). Second, activity-travel patterns were recorded also after the provision of the PTP in a second week (post-implementation) in order to test the proposed personalised plans and enable mobility advisors to monitor "post" strategy behaviour. Comparison of the patterns collected before and after enabled us to conduct an exploratory analysis of variations in time use and activity-travel participation for different time frames (weekly, daily and single episode).
Spatial information collected with the GPS was used to quantify the distances travelled by all modes of transport (motorised and non-motorised), providing a further element for evaluating the effects of the VTBC implemented and in particular allowing us to compare the distances travelled with the different options, before and after PTP provision.
Third, intra-variability related to personal activity-travel patterns before and after intervention, was detected by monitoring behaviour over several days. In addition, as already mentioned, further involvement of the participants kept alive their commitment contributing to the success of the measure.

3.1 The device

The system used in the VTBC program for data collection, the so called Activity Locator (see Meloni *et al.,* 2011; Spissu *et al.*, 2011), comprises (1) a client software installed in a portable GPS integrated device (smartphone, Figure 1), (2) a server software that transmits and receives information to/from each client, and (3) an Internet connection. The client software is a Java application that can be installed in any smart phone (Symbian, Android and IOS6 platform) with built-in GPS currently available on the market.
The application enables to track individual daily routes and to collect all activity-travel related information through a sequence of pull-down menus that reproduce the classical activity diaries (Figure 2). The main difference with traditional activity diaries is that activities are recorded in real time, instead of at the end of the day on returning home.
The application is accessible from the cell phone "home" screen, pressing a dedicated key, and is designed to send automatic pings every 5 seconds containing only positioning data (latitude, longitude, time) and manually inserted attributes of activities and trips.
The server software collects the information sent by each client. Each user can be identified in real time on a map (powered by Google Maps) by a symbol containing all the user information (*i.e.* spatial, temporal, and activity information codes) (Figure 3). The data are immediately available in database formats (*i.e.* xls, csv, xml) and downloadable onto any desktop or laptop computer. The data are transferred by each client to the server and vice versa via an Internet connection. In addition, the server software is designed to send a variety of information to the clients such as traffic information and survey requirements.
The system can be used as hybrid, if the users keep the application open but do not manually insert the activity-travel attributes. In this way, GPS route tracking can still be recorded in the server and the activity-travel attributes will be indicated using traditional activity-travel diaries.

Figure 1 – Smart phone

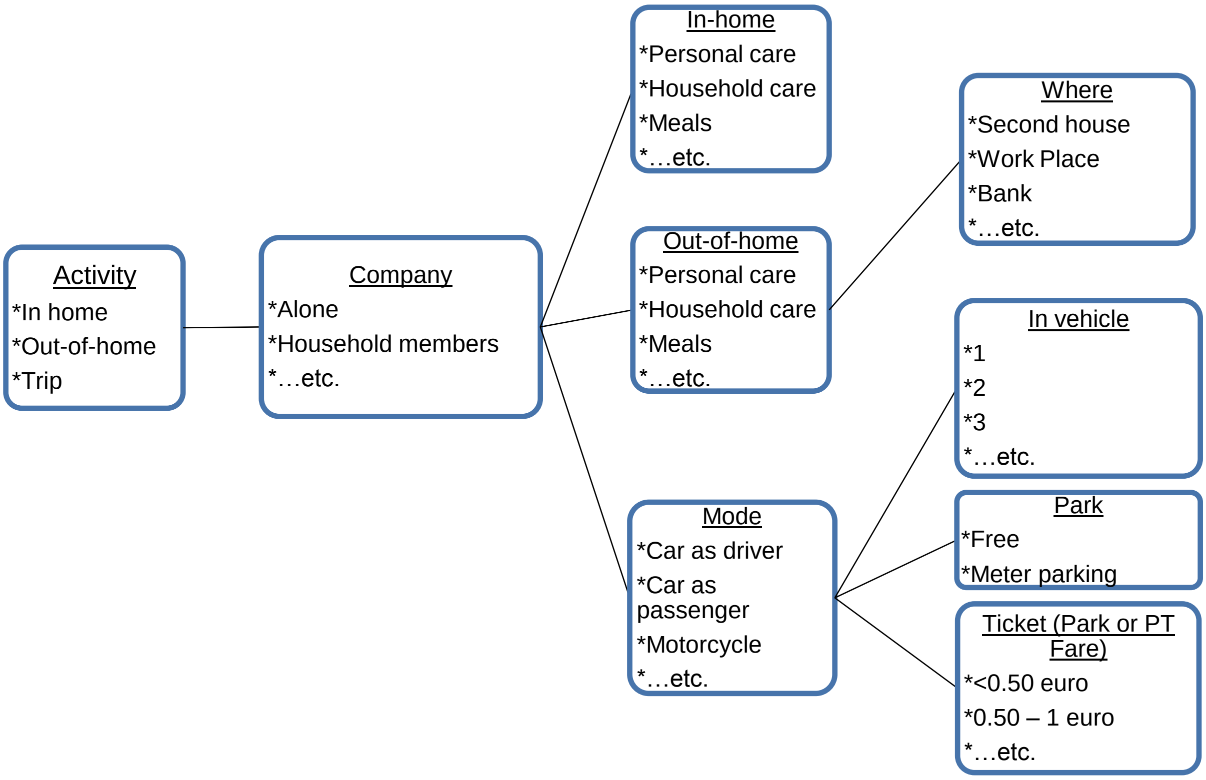

Figure 2 – Client application scheme

Id	Date	Beg	End	Type	Purp.	Mo./Wh.	Lat	Long	IV	P	Tckt	Comp
4	07/04/2011	20:14:03	21:09:50				39.2311	9.1888				
4	07/04/2011	21:09:50	21:10:07				39.2364	9.1997				
4	07/04/2011	21:10:07	21:10:45				39.2358	9.2012				
4	07/04/2011	21:10:45	21:10:51	2	21	28	39.2379	9.2028				26
4	07/04/2011	21:10:51	21:11:06				39.2378	9.2013				
4	07/04/2011	21:11:06	21:11:21				39.2378	9.2013				
4	07/04/2011	21:11:21	20:30:00				39.2378	9.2013				
4	07/04/2011	20:30:00	21:11:32	2	21	28	39.2378	9.2013				25
4	07/04/2011	21:11:32	21:11:44				39.2362	9.2001				
4	07/04/2011	21:11:44	21:11:52	3		43	39.2311	9.1888	53	58	61	24
4	07/04/2011	21:11:52	21:12:02				39.2235	9.1956				
4	07/04/2011	21:12:02	21:12:07				39.2281	9.2121				
4	07/04/2011	21:12:07	21:12:12				39.2281	9.2121				
4	07/04/2011	21:12:12	21:12:17				39.2311	9.1888				

Id	Id user
Beg	Begin time
End	End time
Type	Type of activity (In-home , out of home; trip)
Purp.	Purpose
Mo./Wh.	Mode of the trip or type of location for out of home activities
Lat	Latitude
Long	Longitude
IV	N. of people in the vehicle
P	Type of parking lot
Tckt	Ticket (for Transit or for Park)
Comp	Company

Figure 3 – Server different Information

In particular, in order to compare real time data with the deferred information, for two workdays in the survey the same individuals were asked to carry the smartphone as a regular GPS ("GPS-only") and to report by phone the entire series of activities and trips at the end of the day to a team of mobility supervisors (a hybrid system). Note that, for both survey methods (Activity Locator vs. GPS-only) three mobility supervisors monitored participants throughout the survey days, contacting participants to ask them to specify/correct inconsistent or missing data where necessary. The main difference in the phone calls was basically related to the amount of information requested and therefore to the duration of the call. When the AL was used, the phone call at the end of the day was quick and it was easy for the mobility supervisor to complete the entire activity-travel pattern. Indeed, most of the activity and trips performed during the day had already been reported by participants in real time. When GPS-only was used, the phone calls were instead longer as participants were required to report the entire activity travel pattern. In this case, errors other than omissions and system errors are difficult to detect as the mobility supervisors have little or no available information to detect data inconsistencies.
It is important to note that, the activity locator was an important component of the study, making it possible to collect highly detailed information immediately available for preparing the PTP. Further, the smartphone itself having attractive applications served as an incentive for participation. The interaction with the software application created a daily routing of tasks that engaged the participants during the program.

4. RESULTS

The sample gathered reflects the actual distribution of the current population living in the area near the railway line. Participants were equally divided between males and females

(50% males, 50% females), and among age groups: the whole sample was uniformly distributed among 18 – 30 (36%), 31 – 40 (31%) and 41 – 80 (33%). The sample was composed mainly of workers (employees (51%), self employed (25%)) students (19%) and unemployed (5%). Most of the participants were not married (54%) and children were present in 28% of the households. Regarding household characteristics, the sample was distributed as follows: 1 – 2 people (36%), 3 – 4 (54%), 5 and more (10%). All participants had a driving license and own a car (this was a requirement to participate), but the kilometres travelled annually varied significantly among participants: 50% travels less than 15,000 km, 26% 15,000 – 25,000km, 12% more than 25,000 km and 12% didn't know. Lastly, 69% of households owned from 1 to 2 cars and the remainder 3 or more.

The rest of this section describes the results of a comparative analysis between data collected through the Activity Locator used as an active logger and the same device used as a hybrid system. The main implications of the two types of collected data are on the creation of accurate PTP while the system itself had important role on engaging participant for the entire duration of the program and on the decision to change travel behaviour. Therefore the first two sub-sections will report an analysis of the accuracy of collected data, while the last one will analyze the effect of the active logger on travel behavioural change.

4.1 Ability to reproduce activity-travel patterns

This section describes the implication of AL use on the quality of activity-travel data comparing real time and deferred activity-travel attributes. In order to conduct a more accurate comparison only the same days over the two weeks of the survey were considered in the analysis. In particular days were selected on the basis of GPS-only usage of the device for each participant and then compared with the same days monitored with AL. Finally, a total of 218 observations days for GPS-only mode (2 days x 109 participants) and 218 for AL mode were considered. We also carefully checked that the travel patterns for these days (with AL and GPS-only) were similar, in order to avoid that detected differences were due to differences in the type of activities performed.

The following analyses report the observed values in the AL days (first block), in the GPS-only days (second block) and the related variation (third block), with respect to participation (P in the following tables), duration and number of episodes per day (epi/day in the following tables).

As shown in Tab. 1, the average daily time spent in in-home and out-of-home activities are quite similar (+2% for activities in the home and -1% for those out-of-home), as well as the number of activities reported. As regards trips, the table shows instead that on the GPS-only days both the duration and number of episodes reported is lower than for AL days (-11%, -14% respectively). This result seems to confirm the underreporting of short trips in traditional survey (Stopher *et al.*, 2004).

Tab. 1 - Daily activity time allocation

	AL			GPS-only			Variation %		
	P	Duration (min)	Epi/day	P	Duration (min)	Epi/day	P	Duration (min)	Epi/day
In home	100%	890.04	7	99%	904.95	7	-1%	+2%	0%
Out of home	94%	473.78	4	93%	470.92	4	-1%	-1%	0%
Trips	94%	111.06	7	93%	98.89	6	-1%	-11%	-14%

Looking at the activity duration divided by purpose (Tab. 2), it is interesting to note that among in-home activities personal care and discretionary activities are reported as having shorter duration during GPS-only days, compared with AL days. On the contrary, time spent for meals and work/study activities is higher in GPS-only days, suggesting an overestimation (particularly for work/study activities, +20% in GPS-only days, corresponding to the same number of episodes). For out-of-home activities, the time reported is generally higher on GPS-only days, compared with AL days (except for shopping, -6%). The highest differences were detected for personal care activities (+30%, with an underestimation of episodes, -9%) and Pick up / Drop off (+50%), probably the latter due to an overestimation of waiting time (episodes reported are similar, +1% in GPS-only days).

Tab. 2 - Daily activity time allocation by purpose

	AL			GPS-only			Variation %		
Activity type	P	Duration (min)	Epi/day	P	Duration (min)	Epi/day	P	Duration (min)	Epi/day
In home									
Personal /Hhold care	95%	111.2	1.9	96%	107.1	1.8	+1%	-4%	-5%
Meals	90%	121.1	2.0	94%	129.4	2.1	+4%	+7%	+3%
Work/Study	27%	257.2	1.5	23%	308.8	1.5	-15%	+20%	0%
Discretionary	55%	141.7	1.3	57%	132.8	1.2	+4%	-6%	-5%
Sleep, relax	99%	533.6	2.1	99%	531.3	2.1	0%	0%	+2%
Out of home									
Personal /Hhold care	32%	72.4	1.5	30%	93.9	1.3	-6%	+30%	-9%
Meals	49%	75.8	1.4	53%	77.4	1.3	+8%	+2%	-10%
Work	83%	390.7	1.9	80%	401.6	1.9	-4%	+3%	+2%
Discretionary	44%	108.9	1.3	32%	113.4	1.3	-27%	+4%	-4%
Shopping	24%	41.3	1.4	19%	38.6	1.2	-21%	-6%	-17%
Pick up/Drop off	29%	8.3	1.6	30%	12.5	1.6	+3%	+50%	+1%

Regarding travel behaviour by mode (Tab. 3), interestingly of all the different modes that registered a level of participation equal to or higher than 20% (motorcycle, bicycle, urban bus, train all registered lower participation on the days considered) the average number of trips per day was lower than those monitored with the AL, indicating that on GPS-only days it is difficult to recognize the entire series of trips made by the user. On GPS-only days, in some cases, the same trend also emerges when greater distances are travelled, confirming that users tend to omit short stops in end of day reporting.

With regard to car as driver mode, a difference of -16% in average number of trips per day and -21% of average distance travelled per day is detected in GPS-only days. This difference can of course be attributed to actual differences among days or participants (-6% in the number of episodes reported), but it can also be related to a certain extent to inaccuracies in reporting parking times and general driving-related times that instead are easy to detect when activity attributes are entered in real time.

Only the travel time by car as passenger has a longer duration (+63% in duration and +12% number of episodes) when recorded with GPS-only system. The number of trips, duration and distance is also underestimated for the walking mode compared to real-time recording.

Light rail registered the same number of trips, but of shorter duration (-7%) and distance (-2%).

Tab.3 - Daily travel behaviour by mode

	Travel Attributes	AL	GPS-only	Variation%
Car as driver	Participation	83%	81%	-2%
	No. Trips	4.3	4.0	-6%
	Average Duration (min)	83.8	70.7	-16%
	Average Distance (km)	39.6	31.1	-21%
Walking	Participation	52%	49%	-6%
	No. Trip	4.6	4.2	-9%
	Average Duration (min)	30.7	24.5	-20%
	Average Distance (km)	1.7	1.6	-10%
Car as passenger	Participation	20%	19%	-5%
	No. Trips	2.1	2.4	+12%
	Average Duration (min)	36.9	60	+63%
	Average Distance (km)	16.0	28.4	+77%
Light Rail	Participation	22%	20%	-9%
	No. Trips	2.0	2.0	0%
	Average Duration (min)	29.6	27.7	-7%
	Average Distance (km)	8.7	8.2	-2%

4.2 Error Analysis

In this section, we describe the analysis of errors due to misreported activity data and system-related errors for the comparable AL/GPS-only days. Misreported activities include omissions, inconsistencies and deferments in manually reporting activity and trip attributes, while system errors are mainly due to technical issues such as canyon effects, signal reflection, and smart phone battery life. Further, internet errors related to connection issues that prevented data transfer between smartphones and the server are also highlighted.

Tab. 4 shows the average number of compilation errors committed by participants, distinguishing between real-time compilation (AL) and end of day reporting (GPS-only). Although on GPS-only days the number of omission errors are lower than on AL days (-15%), a higher number of inconsistencies were detected (+48%), probably due to respondents' memory lapses. Similarly the average number of GPS system errors is higher

(+29%) on GPS-only days. This latter result indicates a negative effect on activity travel pattern accuracy when participants are not required to check the survey device (GPS-only usage). To confirm this, the average number of interventions by the supervisor for path reconstruction increases in fact by 69% compared to the days when the device is used in the classical way (AL).

Tab. 4- Daily number of errors per participant

	AL	GPS-only	Variation %
Omissions	4	3	-15%
Inconsistencies	2	3	+48%
System Error	4	6	+29%
Reconstructed records	18	31	+69%
Deferment (AL)	2	-	-

Figure 4 shows the percentage variation of errors between GPS-only and AL compilation for different activity types (in-home, out-of-home and trips). Analyzing the trend of errors one can observe that the negative variation of omissions (see Figure 4) is mainly attributable to in-home and out-of-home activities. In fact, it is possible that participants did not perceive changing from one type of activity to another, while when asked by the supervisor at the end of the day they were more inclined to list each single activity. Note that in-home activity system errors are higher than for out-of home activities. This may be due to the fact that the GPS system does not work properly inside buildings, while some out-of-home activities were held outdoors, where the GPS in general works properly. As regards trips, the three errors common to the different compilation types are generally higher during GPS-only days.

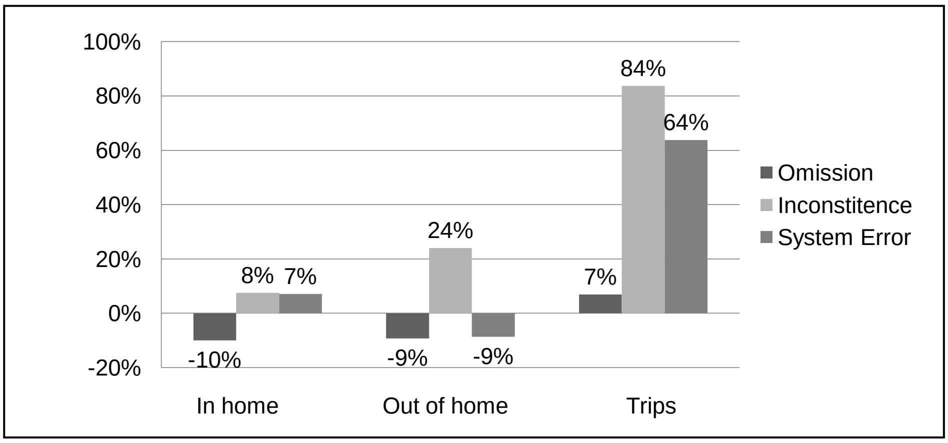

Figure 4 - Percentage variation in errors per activity type

Figure 5 shows the percentage variation of errors between GPS-only and AL compilation for different travel modes with a level of participation equal to or greater than 20% on the days considered. Also, considering for simplicity the errors common to the two types of detection, we can observe in general on average a higher number of errors on GPS-only days. System error is on average higher for GPS-only for the three considered modes (except for walking trips), omission and inconsistencies in reporting trips at the end of the day are also higher, except for the light rail mode, which is probably scheduled by the user because of its frequency, and therefore not easily forgotten by respondents.

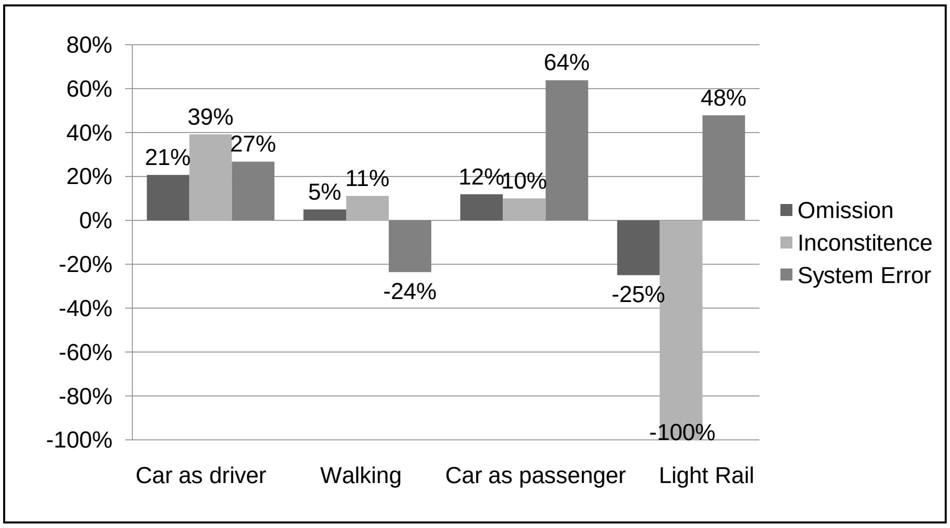

Figure 5 - Percentage Variation in errors per trip mode

4.3 Participant feedback

At the end of the two-week survey each participant was required to express his/her opinion regarding the use of the Activity Locator, participation burden and the most frequent problems that arose with the device. They were also asked to self-evaluate the quality of the data provided in the classical mode (AL) compared to the GPS-only mode.

Concerning the effort required, 61% of participants stated that the system was not burdensome, 23% that the burden was due to constantly having to enter activities and trips performed in real-time, and 16% that it was due to the technology (probably individuals unfamiliar with applications and smartphones).

On the other hand, 75% stated that the technology was easy to use from the beginning, 24% believed that one or two days were enough to learn, while 1% said they found it difficult to use. The problems encountered by users with the device, are those usually reported in the literature for GPS technologies. Lack of GPS signal (66%), battery life (51%), debugging the application (29%) and problems with internet connection (8%) are the most frequent problems found. All participants stated that the daily interaction with the supervisor was not a problem.

Comparing real-time (classic use of the Activity Locator) and end-of-the-day compilation (device used only as a GPS), 55% of users stated they had been more precise in real-time mode, 24% at the end of the day, 12% did not find any differences between the two types of compilation, while 9% did not know (Tab. 5).

Tab. 5 – In which type of data collection were you more accurate?

	N	%
In real time (Activity Locator)	60	55%
At the end of the day (GPS-only)	26	24%
Same accuracy	13	12%
Don't Know	10	9%
Total	109	100%

As mentioned before, the active logger used in the program played the dual role of serving as a tool for highly detailed data collection and as an incentive to engage the participants and heighten their travel awareness.
Indeed, only 12% of the participants who at the end of the program changed their travel behaviour (*i.e.* used the light metro) stated that they preferred "end of the day" compilation (GPS-only), while those whose did not change, or who stated the intention to change in the weeks to come, were slightly more in favour of the GPS-only system (respectively 25% and 27%). On the other hand, 85% of those drivers who changed their behaviour did not consider the device burdensome, as opposed to 56% who stated they would change in the weeks to come and 50% of those who did not change. This finding highlights the very significant relationship between participant commitment and the results achieved in travel change behaviour decisions. Summing up, 90% of participants who preferred the activity logger to the GPS-only mode changed their behaviour (29%) or stated the intention to change in the weeks to come (61%), while the remaining 10% did not accept the suggestion to use the light rail.

5. DISCUSSION AND CONCLUSION

The present work describes the implications of using an Active GPS Logger to collect temporal-spatial activity-travel data during a VTBC implementation. Analysis of the data collected showed a good degree of detail (number and duration of the different types of activities and trips) and a high degree of confidence (variations in time allocation and participation) in the two survey weeks.

The Active Logger used in this work made it possible (1) to collect all daily activity-travel patterns and all related attributes, (2) to track of all routes covered, combined with activities information (purpose, location, duration, company) and travel information (mode used, duration of the trip, company, number of people in the vehicle, tickets/parking fees, *etc*.). Furthermore, the use of the device for several days in the pre-implementation phase (week 1) as well as in the post-implementation phase (week 2), allowed us (3) to detect intra-variability in activity-travel patterns between the before and after phase, with a high level of detail (distance travelled, travel mode, number of trips made as well as activity chaining over space and time).

Further, a comparison with a two-day GPS-only survey highlighted the ability of the device (1) to collect highly accurate data, (2) to contain the number of errors and (3) to motivate participants to greater commitment and accuracy in the compilation.

The main findings showed that in the GPS-only survey participants stated longer durations of out of home activities compared to those recorded in real time (particularly for personal/household care (+30%) and pickup /drop off activities (+50%)). A greater number of trips were recorded on the AL days, indicating, as expected, difficulty in recalling the entire sequence of trips made at the end of the day (GPS-only survey). Looking at the errors detected during the two different types of surveys, the Activity Locator involved less errors mainly because the continuous interaction of the users allows them to detect problems such as for example the lack of signal detection.

Finally, 55% of participants stated greater accuracy in the real time collection mode, confirming that despite the greater burden, this method is perceived by participants as more precise. In addition, this accuracy is functional also to travel behavioural change. The majority of the active loggers sustainers (90%) changed their travel behaviour in the second week (29%), and 61% stated the intention to change in the weeks to come.

Further research will extend the program to a larger sample of individuals, and to a wider range of sustainable modes (bus, bicycle, *etc*.). Finally, the Activity Locator is currently being implemented for the Iphone platform and other smartphones with more advanced GPS modules are also being considered.

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