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Quantifying the Relation between Activity Pattern Complexity and Car Use Using a Partial Least Square Structural Equation Model

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Abstract: This paper studies the relationship between activity pattern complexity and car use using two multi-day surveys involving the same participants but collected just before and about one year after they relocated their workplace. Measurable characteristics related to two latent variables, namely activity pattern complexity, or trip chaining (e.g., number of activities done within and outside the home–work tour), and to car use (e.g., usage rate, distance travelled by car) were selected. The study shows that the methodology adopted, partial least square structural equation modelling, quantifies the relation between the two variables, and is robust towards changes in important contextual characteristics of the individuals, namely workplace location. The findings indicate that the number of activities chained to commuting travels strongly impact mode choice and, in particular, car use. The paper also shows that chaining non-work-related activities has a stronger impact on car use. The results of this study suggest that planning and management solutions aimed at reducing car use, but focusing only on the commuting trip while neglecting the impact of other daily activities, may be less effective than expected.

Keywords: trip chaining; mode choice; structural equation modelling; multi-day survey; workplace relocation

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1. Introduction

Sustainable mobility is an established goal for urban planners and policy makers. Policy measures aim to achieve reductions in, e.g., trip distances and car use, and more generally to achieve greater efficiency in the use of cleaner transportation services. In addition, national policies often promote mobility management solutions adopted by employers, such as parking restriction policies at job locations, financial support for seasonal transit passes, etc. In many cases, these policies target the reduction of car trips, and especially commuting trips that are considered the main responsible factor of morning and evening congestion. However, commuting is a critical part of the daily travels, and one cannot neglect how it is embedded within, and constrained by, the daily routine. Complex activity tours, including, e.g., picking up or dropping off a child at school, and performing shopping or sport activities, may impede workers from using public transport or active modes for commuting despite, e.g., having to perform a short home–work distance. Very strict sustainable mobility measures discouraging the use of the car and neglecting the daily constraints and activities of individuals may result in an overall loss of satisfaction [1,2].

Analysing the impact of activity–travel patterns is a necessary step to understand commuting mode choice [3–6]. In this study, a quantitative analysis of the trip chains' impact on car use by looking at the case of a large employer, the University of Luxembourg, was performed. The analysis relies on two waves of a dedicated multi-day survey and adopts a structural equation modelling (SEM) approach [7]. More specifically, partial least square SEM (PLS-SEM), which deals with the complex interactions between activity patterns, individuals' characteristics and mode choice, is adopted. The collected datasets present unique features, making them very valuable for this analysis. First, they describe a single employer, with all individuals sharing the same work location. Second, the two waves have been collected exactly one-year apart. In between this period, the staff moved to a new workplace. This makes it possible to test the robustness of PLS-SEM to variations in an important contextual characteristic such as the workplace. This finding suggests that SEM may be a more robust methodology towards contextual changes such as workplace relocation for assessing the impact of trip chaining on mode choice, in contrast to random utility-based approaches [8,9].

Therefore, this paper has two major contributions:

1. It quantifies the relation between variables representing the complexity of activity chains with car use characteristics. Despite the chosen methodology working well with small sample sizes, socio-demographic variables need to be controlled for. Therefore, the study provides insights into the importance of socio-demographic characteristics (gender, age, family composition, etc.) on the said relationship.
2. It demonstrates the robustness of PLS-SEM towards important variations in the dataset. More precisely, the quantified relations are shown to not change significantly even if all individuals have relocated their work address. Moreover, the model was calibrated on the two waves, considering all days of the individuals as uncorrelated, an acceptable assumption given the low multi-collinearity quantified in the datasets, as well as using a single day of the week. Results of the model are found to be consistent.

Apart from the above contributions, the analysis reveals the strong impact of chained activities within the home–work tour. In particular, including non-work-related activities, such as dropping off children at school or shopping, has a significant effect in increasing the number of car trips.

The paper is organized as follows: in Section 2, a review of the literature on the impact of trip chaining complexity and mode choice is performed; the modelling approach and the case study are introduced in Section 3, whereas Section 4 presents the main results and discusses implications in terms of policy measures. Finally, Section 5 provides conclusions.

2. Literature Review

Mode choice is a complex process involving many interacting parameters [10–12]. While land use and the context are considered as major determinants [13], other factors, such as lifestyle, perceptions, habits and trip chaining, the main focus of this work, have been found to be also equally relevant factors. As emphasized by Timmermans et al. [5], during a typical day, individuals make decisions related to their activity pattern: people choose the activities they want to perform (as part of tours, or not), where, at what time, for how long, and with which mode they will use to reach the activity.

Empirical studies reported that a small share of daily activity–travel patterns is restricted to the simple home–work–home tour, whereas the majority includes at least one more chained activity [14]. Workers combine commuting and out-of-office trips to avoid time losses and maximize their overall daily utility. By adding one or more activities before and/or after work, individuals and households can save up to 15% of their total travel time [15]. However, an increasing complexity of trip chains is often associated with higher car dependence, since the flexibility and convenience of a car is perceived as an asset to perform non-simple activity sequences [16]. By modelling trip chaining and mode choice as a sequential process using a bivariate probit model, Ye et al. [16] suggest that the complexity of the activity pattern tends to drive the mode choice rather than the opposite. This is in line with Krygsman et al. [6], who reported, using a co-evolutionary approach, that mode decisions are most often adjusted to decisions related to trip chaining, and not the opposite.

McGuckin et al. [17] indicated that public transport commuters are almost twice as likely to perform direct home–work–home trips, and that long-distance commuters have a higher propensity to include a non-work-related activity before going back home. Lee and McNally [18] highlight the possibility for individuals to perform activities opportunistically, e.g., short activities included within their commuting. Adler and Ben-Akiva [3] and McGuckin et al. [17] highlighted the importance of considering socio-economic characteristics. The household structure affects the number of undertaken activities [19,20]. Having dependent children could lead, for instance, to perform more complex activity patterns, especially by women [17,20].

Daisy et al. [21] focused on quantifying the relationship between activity–travel pattern complexity, or trip chaining, and mode choice and categorised trip chaining into 19 travel tours and related them to 10 mode/multimodal choices. They found socio-demographic variables, urban form, and residence location to be strong determinants, but also that more complex tours are linked to higher car usage. The data used in their research concerned Canadian residents, whereas similar studies and analogous findings were also reported for Mexico City by Bautista-Hernandez [22], for Copenhagen by Thorhauge et al. [23], and using a multi-day survey from Ghent, Belgium in Scheffer et al. [24]. The work by Md Tazul and Khandker [25] is the only one to the authors' knowledge that employed SEM, and it differs from this work as it focused on resource ownership necessity (possessing a personal car and/or a bike) and activity participation flexibility.

The methodology used in this work, SEM, has been used to study trip chains for both work and non-work-related tours to reveal the main factors driving mode choice in Switzerland [25], and in developing countries [26]. This work contributes to this stream of research by providing additional insight into the relation between activity pattern complexity and car use, and by showing the robustness of SEM towards contextual changes.

3. Methodology

This study aims to quantify the impact of activity pattern complexity (APC) on car use (CU). These variables are complex constructs, each bearing multiple dimensions. They can therefore be considered as latent variables derived from a set of simpler measurable indicators. To model their relation, SEM is the methodology adopted. SEM is a technique that was developed in the 1970s [27], and later adopted into the transportation field [7].

SEM quantifies linear relationships between cardinal variables and estimates the elasticity of a certain (latent) variable for a change in another (latent) variable. The advantage of SEM compared to regression analysis is the possibility to work with chains of relations between measurable variables and latent variables, i.e., complex concepts or ideas not directly observable, and to quantify direct and indirect effects to and from these variables [12]. Another advantage with respect to alternative travel behaviour methods (e.g., discrete choice models) is that collecting information on non-chosen alternatives is not needed, which would be a rather challenging task for this particular study. Since SEM focuses on quantifying the significance of interrelations between variables, and causal-effects estimations, it has also been often used as first step in econometric and travel behavior models [28].

Two components are distinguished: (1) the structural model showing causal dependencies between endogenous and exogenous variables, and (2) the measurement model showing the relations between latent variables and their indicators. Relations can be assumed as reflective, i.e., when the indicators of a construct are considered to be caused by that construct, or as formative, when the measured variables are considered to be the cause of the latent variable. In this study, the direction of the causality, i.e., from the indicator to the latent construct, and the various themes covered by some indicators for a single latent construct were important elements that led us to opt for formative constructs. This is in line with Banerjee and Hine [29], who stress that, while most transport studies using SEM have used reflective constructs, many constructs in the transport domain remain strictly formative. While covariance-based SEM (or CB-SEM) is the standard approach to estimate models with reflective latent variables, partial least square SEM (PLS-SEM) is recommended when formative constructs are adopted [30,31]. In addition, while CB-SEM aims at minimizing the difference between the sample covariance matrix and the model covariance matrix, PLS-SEM aims at maximizing the explained variance of the dependent latent constructs [32], making it more suited for this study. Another advantage of PLS-SEM is that it can work with small sample sizes and handle complex models with a multitude of paths and categorical indicators in comparison to conventional SEM [32]. Additionally, multiple latent variables can be estimated (e.g., [23,28,33,34]).

Past studies reported that SEM lacks robustness towards variations in the dataset and in assessing the statistical significance level, especially when dealing with correlated variables [35]. In order to test robustness, the model results using data from the same respondents at two different time periods, differing only for the workplace location, were compared and found to be consistent. In addition, the model was evaluated using more than one fitting metric, as suggested in Yuan and Bentler [36]. The authors believe that these two extensions of the analysis provide solid ground for showing the validity of the results and, in general, of the robustness of the PLS-SEM approach.

Due to data limitation, the effects of land use variables (urban form and density) could not be included in the analysis. Another limitation to be highlighted is that, although SEM works well with small databases, the collected dataset had to still be inflated to obtain statistically significant results. To partly mitigate the issue of a limited number of individuals and their specificities in terms of socio-demographic characteristics (all university staff members), a multi-group analysis was performed (see Section 4).

3.1. Case Study

Luxembourg is a small country facing big mobility challenges. While 76% of the workers commute by car, the share reaches 89% for cross-borders [37]. The congestion is also related to the monocentric development of the country. In order to decrease the traffic pressure, and to reach a more balanced development across the country, a polycentric land development policy has been implemented. The relocation of the University of Luxembourg to the south-west of the country is part of this policy. From 2015, most of the staff was moved from the campuses located within the capital city to a new activity area, which is expected to increase the attractiveness of the surrounding cities, thus, in the long run, favouring the expansion of the whole region. Effects of these land use decisions in terms of mode shifts, residential choices, and on spatial characteristics of activity–travel patterns have been analysed in [38–40].

Between May–June 2015, prior to the relocation of some staff members, a multi-day survey collection was implemented. Respondents provided information regarding their activities (type, location, duration) and the associated trips (travel time, modes) using a dedicated platform, and new data was inserted every time participants were leaving a building. Respondents also provided information regarding socio-demographic characteristics (age, gender, work position, etc.) and level of satisfaction regarding their commuting modes and travelling experiences [1,2,40]. Although the dataset is rather old, its uniqueness in containing the same respondents at one year difference and with workplace relocation as main difference, and the type of analysis presented in this work makes it still highly valuable and valid.

The 2015 survey involved 51 staff members (out of around 400 employees) of the Human Sciences Faculty, at that time working at the Campus Walferdange. Statistics of the data collected in 2015 are provided in Appendix A. In September, the faculty was relocated, and all respondents moved to the new Belval Campus (Figure 1).

One year later, the same individuals were re-contacted and invited to repeat the survey. In total, eight people could not participate to the second round for different reasons: two respondents were not available during that period, one was in maternity leave, and five were no longer working at the university. Hence, 43 individuals took part in both waves, which still represents more than 10% of the total moved staff. An additional questionnaire regarding the modification of other elements in their life was also collected. In total, 27 out of the 43 respondents did not report any significant event such as buying a car, home relocation, having a baby, etc.; therefore, workplace relocation was, for them, the main event affecting their commuting and their activity–travel decisions. Conversely, among the respondents, eight people relocated their home address.

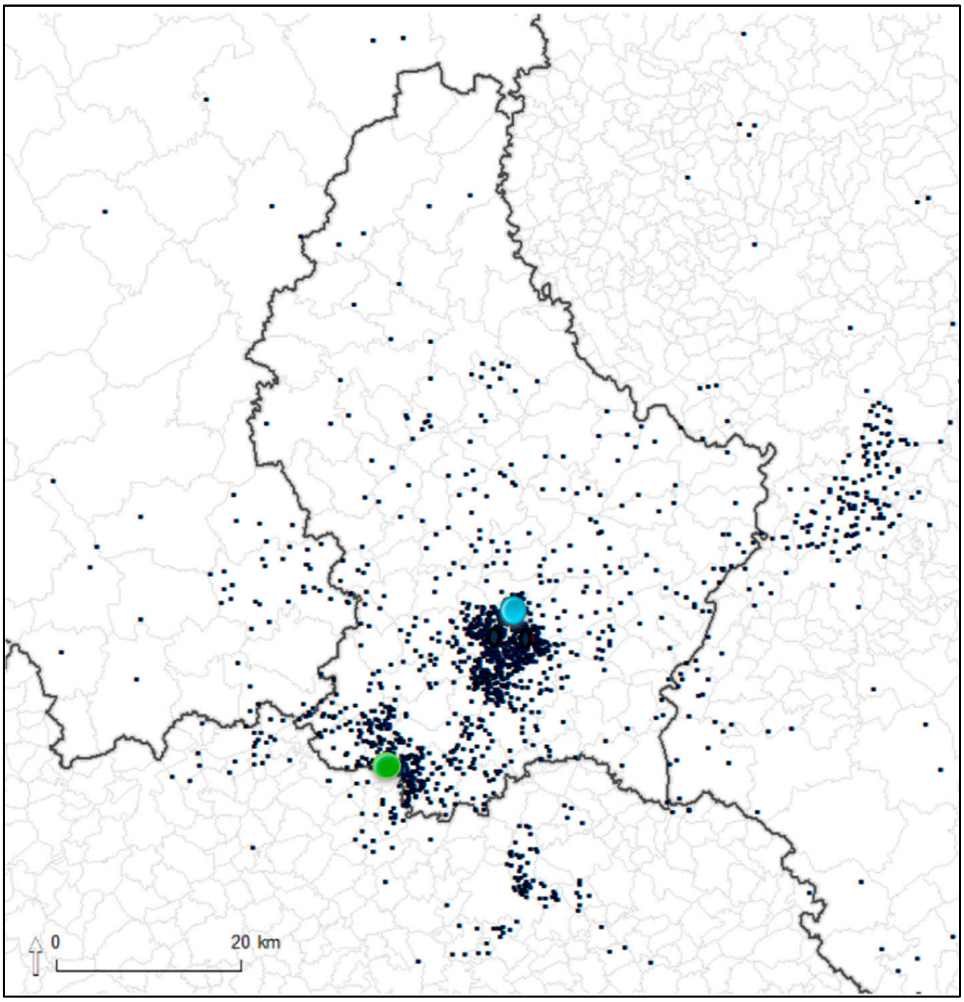

Figure 1. Location of old (blue dot) and new (green dot) workplaces for the respondents. Smaller points show the approximate home of the University of Luxembourg staff members.

Since the focus of this study is on the relation between activity patterns and commuting mode choice, only days where a work activity was described were retained for the analysis. Weekend days, bank holidays, or days without any reported work activity were not considered. For the 2015 dataset, out of the 598 days described by the 43 respondents (i.e., an average of 13.9 days for each respondent), 370 (62%) were retained for analysis while for the 2016 data set, out of the 607 days of information (an average of 14.1 days per respondent), 364 (60%) were retained.

In order to avoid incorrect generalization of the results, one must again stress two specificities of this case study. First, all respondents were, in 2015, working on a peri-urban campus located 8 km north of Luxembourg City, and they were all moved at the same time to the new campus, located 25 km south of the capital. Second, the survey respondents are all highly educated (45% hold a PhD degree, 37% hold a Master's degree) and mostly international workers. Hence, the quantification of the results of the performed analysis cannot be generalized countrywide or readily transferred to other countries, but it is believed that the main conclusions generally hold and are actually not limited to the case of the University of Luxembourg.

3.2. Descriptive Analysis

In 2015, before the workplace relocation, the average home-to-work distance reached 30.2 km, and 14 people had a commuting trip shorter than 10 km. Of course, the distance was different for residents than for cross-border workers. The latter had, on average, a commuting trip of 60.4 km, while residents had an average commuting distance of 15.5 km. In 2016, the average commuting distance reached 38.5 km. Only five survey respondents reported a home-to-work trip of less than 10 km. From the 14 staff members who had, in 2015, a short commuting trip, 12 reported a commuting trip longer than 20 km, and the remaining two had relocated their house. The cross-border workers had, in 2016, on average, a commuting distance of 67 km, while the average trip distance of residents reached 21 km.

In 2015, 57% of the respondents used the car (driving or as passengers) as a main mode for commuting (the longest travel time when a sequence of modes is reported) and 39% travelled by public transportation. These statistics are in line with the university 2012 university staff travel survey [40]. In 90% of the cases, the first mode of the day (when individuals leave home) is also the main mode for the day. This amounts to 95% for cars, suggesting a strong car dependency. In line with Vale [41], 80% of the respondents did not change their main mode despite the workplace relocation. After the relocation, 60% of the individuals did their home-to-work trip by car, 35% using public transport, and 5% by active modes. The commuting time of the respondents shifted from 47 min to 52 min. This increase of 5 min is rather small if compared to a distance increase of 8 km, indicating that average travel speeds also increased.

The respondents reported a median number of 4.1 activities per day in 2015 and 4.2 in 2016. Within the workdays, only 19% of the activity patterns were "Home–Work–Home" (Figure 2). After aggregating all other activity types ("Shopping", "Drop-off / pick-up someone", "Eat", "Learning activity", "Leisure, sport, culture", "Personal business", "Other", "Walking, riding, etc.", "Visit to family or friends") to a single "Other Activity" class, a total number of 86 daily activity sequences, from the simple home–work–home to more complex ones, were obtained.

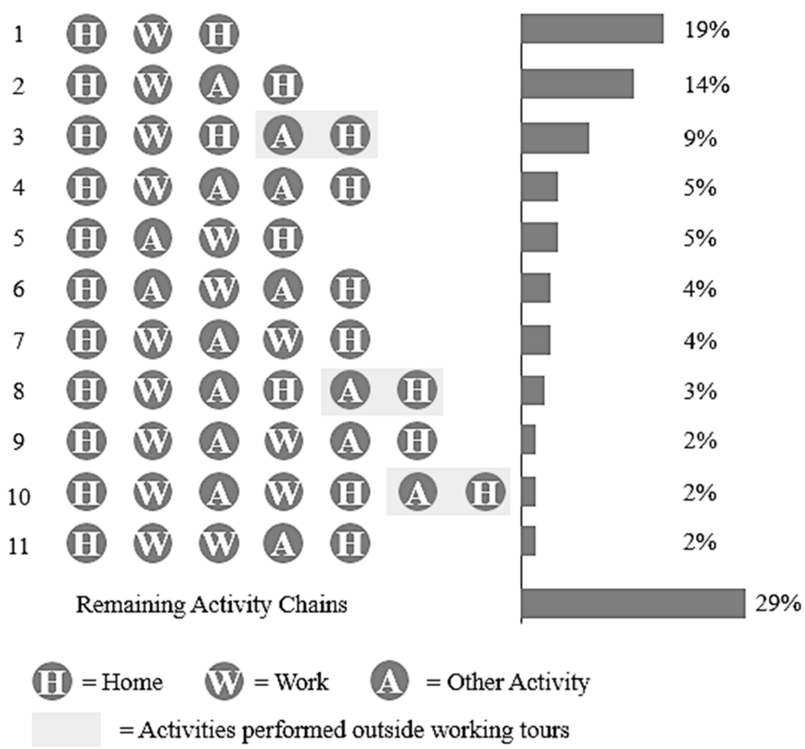

Figure 2. The 11 most recurring activity chains (N = 370 days in 2015).

Important differences can be observed across individuals and across days, for example, one individual conducted 2.5 activities per working day, which is close to a simple daily home–work–home, and another one conducted on average seven activities per working day, indicating a large variation of activity–travel behaviour within the dataset. The respondents reported on average 5.9 different daily activity patterns on the 8.7 described days. The 11 most recurring activity patterns represent 71% of the total activity chains. In total, 9.5% of the total activities were performed outside commuting tours, either in the morning or in the evening. Activity chains of cross-border and internal workers were significantly distinct. For instance, 20.3% of the daily activity chains described by people living in Luxembourg are "H-W-H-A-H", whilst this sequence accounts for only 4.8% for cross-border workers. This indicates that people living closer to their workplace tend to go back home before engaging in a new activity. This finding is in line with [19], who observed that long-distance commuters are often chaining an activity before going back home.

3.3. PLS SEM

3.3.1. Model Specification

To develop the model, SmartPLS, a standalone PLS-SEM software [42], was used. The inner structural model quantifies the relationship between independent and dependent latent variables (in this case APC and CU), whereas the outer measurement model relates latent variables with their observed measurable indicators [43].

Different model specifications were tested, including different measurement models for each of the latent constructs, using combinations of all the indicators available within the datasets. In this paper, only one model specification, which resulted in the highest R-square values (Figure 3), is presented. Other variables such as the number of trips by public transport and by soft modes, as well as travel time and total distance travelled, were tested, but were found not significant. For APC, the duration of the activity was included, which also did not improve the results.

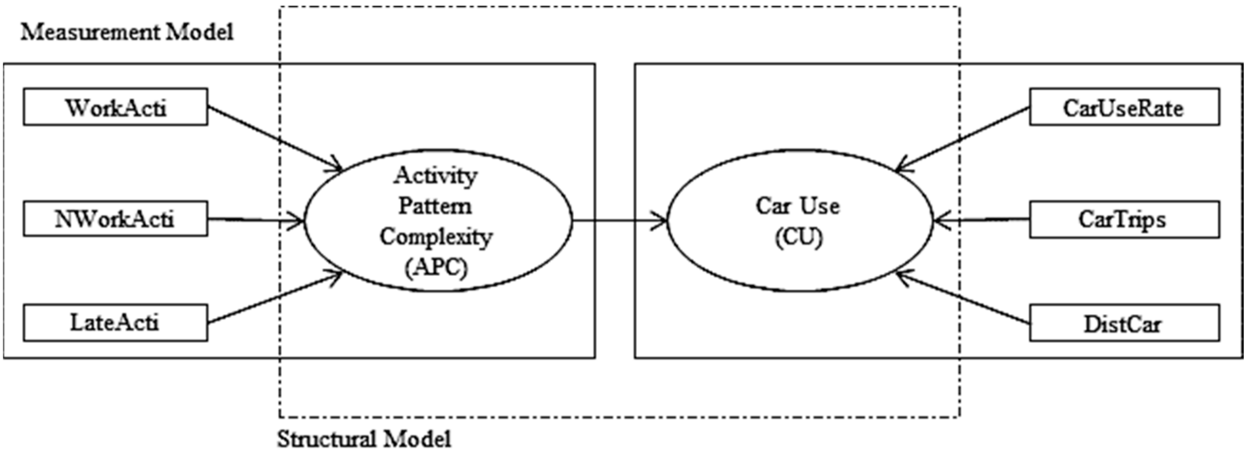

Figure 3. Proposed PLS-SEM model.

Table 1 gives an overview of the measurable variables that were retained in the model. APC is represented by the number of work-related activities, non-work-related activities, and late activities, i.e., those scheduled after 7 p.m. CU is found to be best represented by the share of trips done by car, the distance travelled, and the total number of trips done by car.

As one of the main research objectives of this study is to gain insight into the characteristics related to trip chaining behaviour and their impact on mode choice and in particular on car use, the collection of detailed activity–travel patterns is necessary, and makes it difficult to adopt other approaches such as discrete choice models, which require the explicit enumeration of non-chosen alternatives. Sprumont and Viti [39] showed that, together with the workplace, many other activities chained in the home–work tour have changed location, hence important contextual changes have been reported in the dataset.

Table 1. Variables used in the proposed PLS-SEM.

Indicators used for the car use latent variable (CU)
Distcar: total distance travelled by car over the whole day (All), or within work tour (Work)
CarTrips: number of trips done by car over the whole day (All), or within work tour (Work)
CarUseRate: Share of the total trip done by car over the whole day (All), or within work tour (Work)
Indicators used for the activity pattern complexity latent variable (APC)
NWorkActi: number of non-work activities performed over the whole day (All), or within work tour (Work)
WorkActi: number of work activities performed over the whole day (All), or within work tour (Work)
LateActi: number of activities started after 7 p.m. over the whole day (All), or within work tour (Work)

Regarding dataset size, each collected dataset has a number of respondents that is close to the minimum recommended by Marcoulides and Sanders [44] in marketing analysis. For latent variables formed by two measurable factors, they suggest the dataset to be minimum 52 points. In the 2015 dataset, there have been 51 respondents, while in 2016 this number went down to 43. Hair et al. [45] suggest that the minimum sample size can be dependent also by the significance level of the variables and the final R-square value. They suggest that with small datasets, one can draw reliable conclusions only on variables with high outer loading and weight values, and when R-square is at least 0.25. On the other hand, Hoyle [46] suggest a minimum number of data points of 100 to 200 to be a good starting point, especially when there are intercorrelations between indicators. Following Hoyle [46], in this study, each working day provided by a respondent was considered as the basic unit for the analysis. The days are processed as if they were provided by all distinct individuals, resulting in a dataset of 370 data points for 2015, and 364 points for the 2016 dataset. This pragmatic decision has been taken because the specificity of the available dataset leads to neglect the longitudinal or panel correlation, and can potentially reduce the effect of individuals' characteristics in the modelling results.

On the other hand, adopting this data inflation approach poses questions on the independence and correlations in the data, since mode choices are connected in the trip chain, and also multiple days are collected from the same respondent. Since the paper studies causal (linear) relations, an important aspect that is therefore checked is variable multi-collinearity. Collinearity is not the same as correlation, but actually, in the context of this study and the application of SEM, it is more important to test collinearity than correlation, since it is well known that correlation does not imply causation. By definition, collinearity is when two or more independent variables act similarly to explain the variation in a dependent variable. This is exactly what one wants to avoid in SEM, since SEM is about differentials, not values. To validate these assumptions and account for potential multi-collinearity, the tolerance of variance inflation factor (VIF), which can give an indication of the level of collinearity in the data, was calculated and analysed.

Of course, by including individual heterogeneity in the (panel data) analysis, the explanatory variables are only based on 51 (43 in 2016) distinct individuals. By treating the data as separate points, it is likely that socio-demographic and other explanatory variables' impacts are inflated. To address this limitation, multi-group analysis was performed, in order to consider the effect of socio-demographic variables in the path coefficients. This will also be presented in the next section.

It should be finally highlighted that intra-personal variability concerning daily activity behaviour is important in the dataset and has also been reported in other studies [47]. To partly tackle this limitation, PLS-SEM was run using a working day for each respondent, which, on the other hand, results in a number of points that is slightly less than the recommended minimum, as explained above. Results did not differ significantly, especially in the main conclusions; hence, these results were reported in Appendix B for the 2015 dataset.

3.3.2. Model Validation

As PLS-SEM does not assume multivariate normality, parametric significance tests are not applicable to test if the coefficients such as outer weights and loadings are significant. Alternatively, PLS-SEM uses a non-parametric bootstrapping procedure to test significance. As suggested in Banerjee and Hine [29] and Hair et al. [32], bootstrapping with 5000 samples was used to obtain the required significance levels of the path coefficients, outer weights, and outer loadings.

Data are standardized automatically in SmartPLS, with loadings varying from -1 to 1 (positive values indicating positive correlation between the construct and the indicators). For a well-fitting model, path loadings should be above 0.70. In contrast, weights vary from 0 to an absolute maximum value lower than 1 and represent the partial regression coefficients associated to each loading. If an indicator has a non-significant outer weight and its outer loading is not high, Hair et al. [32] suggest that if the weight value is not higher than 0.50, then the indicator should be dropped from the model, even if its loading is found significant [48]. In empirical practice, if the indicator path loading is not high (<0.5) and is non-significant, the data do not support the contention that the indicator is relevant to the measurement of its factor, and it may be dropped from the model [49].

Following the recommendations from Yuan and Bentler [36] and Hertzog [50], different goodness-of-fit metrics were used. The *p*-values column shows the corresponding significance (probability) levels for the path, while the standardized root mean square residual (SRMR) measures the difference between the observed correlation matrix and the modelled correlation matrix. SMRS has been considered a valid metric for PLS-SEM [51]. Simply stated, the SRMR reflects the average magnitude of such differences, with lower SRMR being a better fit [48]. By convention, a model has good fit when SRMR is less than 0.08 [52]. Ringle et al. [42] indicate that a value of around 0.1 is acceptable. Other goodness-of-fit measures can be used, such as criteria used to assess the model predictive quality including the R-square [42]. The R-square value ranges from 0 to 1, with higher levels indicating higher levels of predictive accuracy.

4. Results and Discussion

Let us first consider the entire daily activity pattern and all travels performed during a specific day (ALL). CU is therefore analysed for the whole day, independent of the activity performed. The second data specification (WORK) considers the activities and travel behaviour observed during only the home–work tour only, thus, in between the departure from home to work and the returning home. Taking the examples in Figure 2, the grey-shaded parts of the activity chains are neglected. Table 2 summarizes the results of the PLS-SEM model for the two datasets.

A significant relation within the structural model was found, since coefficients were around 0.5 for all datasets. Comparing the WORK and ALL datasets, one can observe a slight decrease (from 0.526 to 0.484 in 2015, and from 0.556 to 0.512 in 2016). This is expected, since after returning home and finishing a working tour, respondents have the possibility to use another mode (cycling/walking) to perform later activities. Hence, one can conclude that there is indeed a strong structural relationship between the analysed latent variables. Among the three indicators for APC, the number of non-work-related activities were found to be the most significant factors looking at both outer loading and the relative weight, with a value of around 0.8 for both 2015 and 2016 and for both ALL and WORK datasets, followed by the activities performed after 7 p.m. Intuitively, this factor has significantly less impact on the home–work tour than in the whole daily activity plan, and does not clearly contribute to the path coefficients (lower weight values and limited significance for the home–work tour model). This is essentially due to the fact that working tours described by the participants contain many activities starting at 7 p.m. or later (average of 0.11 for the work tour data specification, as opposed to 0.89 for the entire daily activity sequence).

Table 2. Fit and coefficient estimates of each PLS-SEM model variation for the two datasets.

SmartPLS Results	2016						2015					
	ALL			Work			ALL			Work		
	Origin. Sampl.	T Statistic	*p*-Values	Origin. Sampl.	T Statistic	*p*-Values	Origin. Sampl.	T Statistic	*p*-Values	Origin. Sampl.	T Statistic	*p*-Values
Path Coefficients												
APC -> CU	0.512	15.274	***	0.556	15.722	***	0.484	18.744	***	0.527	19.005	***
Outer loadings												
CarUseRate -> CU	0.818	26.431	***	0.251	2.498	*	0.832	14.743	***	0.855	37.245	***
CarTrips -> CU	0.995	189.92	***	0.843	36.471	***	0.995	18.113	***	0.990	166.92	***
DistCar -> CU	0.205	2.137	*	0.934	70.059	***	0.458	5.609	***	0.479	7.837	***
NWorkActi -> APC	0.957	52.463	***	0.789	15.258	***	0.971	16.867	***	0.427	4.637	***
WorkActi -> APC	0.707	9.215	***	0.883	64.148	***	0.649	8.080	***	0.480	4.779	***
LateActi -> APC	−0.083	0.684	.	0.295	3.390	***	0.300	2.896	**	0.963	49.736	***
Outer weights												
CarUseRate -> CU	0.147	2.773	***	0.025	0.394	.	0.064	0.872	.	0.146	3.303	**
CarTrips -> CU	0.878	18.712	***	0.537	20.914	***	0.911	9.471	***	0.841	16.533	***
DistCar -> CU	0.030	0.378	.	0.676	16.980	***	0.087	1.284	.	0.088	1.684	*
NWorkActi -> APC	0.806	15.330	***	0.381	9.337	***	0.846	11.507	***	0.853	16.308	***
WorkActi -> APC	0.326	5.439	***	0.613	20.434	***	0.195	2.808	**	0.167	2.524	*
LateActi -> APC	0.018	0.206	.	0.230	3.620	***	0.173	2.054	*	0.230	2.967	*
SRMR												
Saturated Model	0.099			0.058			0.129			0.117		
Estimated Model	0.099			0.058			0.129			0.117		
R Square												
CU	0.262	7.592	***	0.309	7.846	***	0.235	9.214	***	0.277	9.429	***

Significance codes: 0 "***", 0.001 "**", 0.01 "*", 0.1 ".", 1 " ".

The results suggest that more complex activity patterns increase car use, especially when non-work-related activities are chained within the home–work tour. Interestingly, strong correlations were found between APC and work-related activities in 2015 for the WORK dataset (0.963); however, for all datasets, weights were below 0.3, indicating that the relation is rather weak. Finally, there is an important relation between APC and the activities performed late in the day, but the impact represented by the outer weight is less strong (0.326 in 2015 and 0.195 in 2016).

Among the three selected indicators for CU, the distance travelled by car (DistCar) is found to be less important than the number of trips performed by car (CarTrips) and the share of car trips compared to the total trips (CarUseRate) for all datasets. Once again, the weight values difference between the two models suggests a behavioural shift after or before the working tour. Finally, the distance travelled by car is found to be significant in the 2015 dataset, but it does not reach the threshold of 0.5 in any of the models, and weights are low, indicating a weak relation with APC. Hence, having complex activity patterns does not imply that more kilometers travelled by car were observed.

Overall, the models show a sufficiently good fit, i.e., the WORK model performs an SRMR of 0.117 (0.129) and 0.058 (0.099), respectively, on the two datasets, which, as mentioned above, are considered reasonable [36]. It was also found that there was a relative consistency of the outer loadings and weights across the two models, again with a higher significance when only the commuting part of the travel is considered (WORK model). The reported R-square coefficients indicate that CU is reasonably well explained as soon as a correspondence between the activities and the travel is considered: all activities and the entire daily travel mode in the ALL model (R^2 = 0.235) or WORK tour activities and commuting mode in the WORK model (R^2 = 0.277). Similar values have also been found for the 2016 dataset (R^2 = 0.262 and R^2 = 0.309, respectively). Overall, the R-square values are moderate yet equivalent when compared to similar studies [29], and similar values are considered acceptable by Hair et al. [45].

To analyse potential multicollinearity issues in the datasets, the variance inflation factor (VIF) was calculated. Whereas [32] suggests accepting results when VIF is lower than 5, a common rule of thumb is that problematic multicollinearity may exist when the variance inflation factor (VIF) coefficient is higher than 4 [48]. Table 3 shows the VIF values for the two datasets and for ALL and WORK subsets. As one can see, all values are well below the threshold, hence indicating that multicollinearity is not an issue in the analysed datasets.

Table 3. VIF values for the two datasets and the subsets considering ALL and WORK tours.

	VIF			
	ALL 2016	**ALL 2015**	**WORK 2016**	**WORK 2015**
CarUseRate	2.385	3.033	1.327	2.977
CarTrips	2.341	2.743	1.358	2.693
DistCar	1.047	1.286	1.057	1.293
LateActi	1.314	1.375	1.621	1.141
NonWorkActi	1.339	1.394	1.64	1.196
WorkActi	1.045	1.018	1.027	1.051

To study the effect of socio demographic variables, multi-group analysis (MGA), which allows the partial assessment of the effect individual characteristics [31], was performed. Groups included (1) gender, (2) whether respondents are PhD students or not, and (3) whether a resident in Luxembourg or a cross-border commuter, which have been found to be the three most significant characteristics. Other variables, e.g., the presence of kids younger than 12 in the household, were not found significant. This analysis was performed only on the first dataset. Since the socio-demographic characteristics of individuals did not change during the two waves, one expects this analysis not to vary significantly with the 2016 dataset.

As Table 4 shows, the gender dummy variable is significant both for the WORK and the ALL data specification, whereas the effect of APC on CU is also significantly stronger for PhD students than for all types of job positions; however, this effect is not significant for the ALL data specification. Finally, the path coefficient is statistically stronger for residents than for the cross-border workers. While the relationship between the trip chaining and car use is important for the general population, some individual characteristics imply a weakened or a strengthened effect. This suggests that individual characteristics must be taken into account in commuting behaviour not for their own sake, but only because they imply a particular activity pattern or suggest a stronger or weaker response to policy or mobility management measures. To some extent, this is aligned with conclusions drawn by Van Acker et al. [12], Kuppam and Pendyala [20] and Lu and Pas [53], who all stress the importance of socio-demographic variables and their interaction with activity pattern, residential choices, etc.

Table 4. Multi-group analysis: effect of socio-demographic information on the path coefficient.

Effect of gender on path coefficients				
	WorkTour Total Effects-diff (∣Female-Male∣)	*p*-Value	All Total Effects-diff (∣Female-Male∣)	*p*-Value
Activity Pattern Complexity –> Car Use	0.168	0.004	0.154	0.048
Effect of job position (PhD student) on path coefficients				
	WorkTour Total Effects-diff (∣PhD-NoPhD∣)	*p*-Value	All Total Effects-diff (∣PhD-NoPhD∣)	*p*-Value
Activity Pattern Complexity –> Car Use	0.157	0.996	0.087	0.917
Effect of being a resident or a cross-border on path coefficients				
	WorkTour Total Effects-diff (∣Residents-Cross-Border∣)	*p*-Value	All Total Effects-diff (∣Residents-Cross-Border∣)	*p*-Value
Activity Pattern Complexity –> Car Use	0.226	1.000	0.386	0.565

5. Conclusions

In this study, insights into the decision process that relates commuting mode choice and activity–trip chains performed by workers of a large employer, the University of Luxembourg, were reported using two multi-day travel surveys involving staff members whose workplace had changed in between the two survey campaigns.

Partial least square structural equation modelling allowed the confirmation of results from the literature that car use behaviour is strongly affected by the complexity of the daily activity pattern of workers. In addition, the study revealed the stronger impact that non-work-related activities (e.g., dropping off or picking up children, shopping, leisure) have on the use of the car when these activities are included in the home–work tour.

By estimating the same SEM model structure on two datasets, the study showed that PLS-SEM provides consistent values, despite the change in one of the two main anchor points in daily activities, i.e., the workplace, together with the location of many of the activities included in the home–work tour. This is an important finding which indicates that the approach is robust towards variations in the data, and does not depend on the specific context where the data were collected.

Moreover, the study reports that the choice of the car for commuting is affected by activity patterns not only within, but also outside working tours. Individual activity patterns themselves depend on socio-demographic characteristics. Socio-demographic information and activity patterns therefore cannot be ignored when devising employer-based transport policy measures. Although the development and the assessment of classical pull- and push-type mobility management measures have been extensively adopted, these measures are generally focusing on sub-portions of individual activity patterns without embracing their overall complexity.

The findings may suggest different policy recommendations. In line with Ye et al. [16] or Vanoutrive [54], the results point at the need for mixed land use development and multi-purpose activity centres, which should be well connected with public transport. Such a planning strategy should have the specific objective to reduce the public transport "missing link" issue [15]. Facilitating access to various services (shops, leisure, family-related services such as schools or kindergartens) in the direct neighbourhood or within worksites will reduce travel distance to non-work activities and the use of car for commuting without forcing a decrease in the number and complexity of the activity chains.

In the case study, two working activities were sometimes reported in direct sequence, suggesting business trips within work tours. Often, this work-related activity was associated to reaching one of the other campuses. In this context, corporate car-sharing schemes at the workplace appear as an interesting mobility management measure, not only to facilitate business trips.

It should be finally stressed out that this study has been done using a relatively small dataset, and on a very specific type of employer. Future research should make efforts in collecting similar datasets for different types of employers and more generally on a city/regional level, in order to gather a substantially larger and more general dataset.

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Institutional Review Board Statement: The study was conducted according to the ethical principles defined by the European Commission and approved by the Ethical Review Panel (or Ethics Committee) of the University of Luxembourg (ERP 13-007 InCoMMune, 4 October 2013).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original data cannot be shared publicly in accordance with the ethical review panel recommendations and the EU GDPR policy since it contains sensitive personal information that cannot be published on an open policy; however, aggregated data can be provided upon request.

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Appendix A. Sample Description

Socio-Demographic Information				
Surveyed population	51	Administrative or technical staff		25.5%
Male	25.5%	Average age		35
PhD students	29.4%	Presence of kids younger than 12		33.3%
Professors or researchers	45.1%	Cross-borders workers		31.3%
General statistics on the multi-day dataset				
Total days	705	Weekday with working activity (study day)		444
Average day per individual	13.8	Average “study day” per individual		8.7
Total activities	2793	Considered activities		1850
Home	1046	Home		605
Work	565	Work		556
Mobility behaviour (for study days)				
	Minimum	Maximum	Average	Standard Deviation
Travel distance by car (km)	0.0	779.5	49.7	79.7
Travel distance by public transport (km)	0.0	724.4	22.3	68.0
Travelled distance by soft modes (km)	0.0	64.9	1.6	4.5
Activity information (for study days)				
	Minimum	Maximum	Average	Standard Deviation
Activities during a work day	2	11	4.2	1.7
Activity time during a work day (min)	65	1537	601	154
Work activity time during a work day (min)	30	810	469	118
Non-work activity time during a work day (min)	0	1207	131	144

Appendix B. PLS-SEM Analysis with One (Average) Day / Participant (2015 Dataset)

Path Coefficients	**WorkTour**			**All**		
	Original Sample	T Stat.	*p*-Values	Original Sample	T Stat.	*p*-Values
Activity Pattern Complexity -> Car Use	0.556	2.3205	*	0.500	1.873	.
Outer Loadings						
	Original Sample	T Stat.	*p*-Values	Original Sample	T Stat.	*p*-Values
CarUsage -> CU	0.994	1.629		0.992	1.571	
CarUseRate -> CU	0.904	1.673	.	0.927	1.635	
DistCar -> CU	0.429	1.246		0.505	1.453	
LateActi -> ACP	0.227	0.667		0.189	0.497	
NWorkActi -> ACP	0.973	1.647	.	0.939	1.603	
WorkActi -> ACP	0.577	1.523		0.530	1.408	
Outer Weights						

Path Coefficients	WorkTour			All		
	Original Sample	T Stat.	*p*-Values	Original Sample	T Stat.	*p*-Values
CarUsage -> CU	0.818	1.458		0.779	1.358	
CarUseRate -> CU	0.236	1.366		0.229	1.084	
DistCar -> CU	−0.063	0.221		0.029	0.134	
LateActi -> APC	−0.033	0.135		−0.232	0.602	
NWorkActi -> APC	0.886	1.625		0.948	1.571	
WorkActi -> APC	0.253	1.284		0.290	1.19	
Validity Criteria						
R^2 Car Use Behavior	0.309			0.25		
SRMR	0.137			0.131		
Discriminant Validity	0.556			0.5		

Significance codes: 0.01 "*", 0.1 ".", 1 " ".

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