Longitudinal analysis of dynamic relationships between working from home, commute distance, mode preference, and car use

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SHORT SUMMARY

The transition to low-carbon emission mobility has emerged as a key objective, encouraging carbon-neutral lifestyles and shifts from car use to more sustainable modes of transport. Although the role of the built environment and life events on mode shifts is recognized, the impact of working from home (WFH) on modal shifts remains unclear and longitudinal investigations are needed to explore the dynamic relationships. This study provides a six-year longitudinal analysis in the Netherlands, using random intercept cross-lagged panel modeling (RI-CLPM) to separate stable between-person differences from within-person changes over time. The findings show the temporal stability of WFH and car use, while commute distance and mode preference fluctuate. WFH tends to reduce car use, and individuals with longer commuting distance are more likely to do WFH. Gender, age, education, distance to public transport, urbanity, job changes, and childbirth also significantly shape evolving travel patterns.

Keywords: Built environment, Car use, Life events, Longitudinal analysis, RI-CLPM, Working from home

1. INTRODUCTION

The global push for carbon neutrality has intensified in recent years, particularly in the transportation sector, which is a major source of greenhouse gas emissions . Achieving modal shifts to active mobility and public transit can reduce car reliance, improve air quality, enhance public health, and support carbon-neutral urban growth. However, effectively promoting these shifts requires understanding the factors driving car use. The built environment and life events are especially important. As previous studies have pointed out (Ewing and Cervero, 2010; Zhang et al. 2020), urban form, accessibility, and sustainable transportation infrastructure can encourage walking and cycling rather than car use. However, most studies rely on cross-sectional data, limiting insights into causality. Meanwhile, life events, such as job changes, childbirth, or relocation can also influence travel behavior (Wang et al. 2020; Kalter et al. 2021), but few studies have explored how these events interact with changes in the built environment. In addition, many longitudinal analyses use only two or three waves of data, which may not capture long-term effects (Kalter et al., 2021; Tao, 2024).

Working from home (WFH) adds another dimension that can reduce the commuting frequency and distance, mitigating congestion and emissions (Elldér, 2020). Driven by the COVID-19, WFH has reshaped commuting patterns and travel choices (De Vos, 2020; de Palma et al. 2022). However, research findings on the relationship of WFH and modal shifts are a mixture of substitution, complementary, and stimulus effects (Mokhtarian, 1991). Some studies have found that WFH increase non-commuting trips

(Zhu and Mason 2014; Currie et al. 2021), while others emphasize the substitution effect on commuting (Elldér, 2020). These inconsistencies highlight the need for longitudinal evidence to clarify how WFH, as well as changes in the built environment and life events, affect evolving travel patterns. Futhermore, the dynamic interplay among WFH, car use, commuting distance, and mode preference are unclear, which may be the key to explaining the uncertain relationships between WFH and daily trips.

Therefore, this paper investigates the dynamic relationships between WFH pattern, commute distance, mode preference, and car use under the influence of built environment and life events through a longitudinal study of six waves of travel diaries from the Netherlands. By examining these dynamic relationships, we are able to uncover how WFH influences car use over time and whether reductions in commuting distances foster a modal shift towards lower-emission transport options. The model also includes the built environment characteristics and life events, accounting for their critical role in shaping evolving travel patterns. The remainder of this paper is organized as follows. Section 2 presents the data and methods. Results and discussion are illustrated in Section 3. The final section summarizes the conclusions.

2. DATA AND METHODOLOGY

To investigate the dynamic relationships between WFH and modal shift considering the impacts of built environment and life events, we use multiple waves of Netherlands Mobility Panel (MPN) data. This study use six waves of MPN data from 2017 to 2022 and screen respondents who participated in the survey for six consecutive waves. Given that COVID-19 lasted 3 years from 2020 to 2022, we similarly selecte the 3 years before the outbreak for comparison from 2017 to 2019. Because we focus on the modal shift from and to car use, we remove respondents who were under 18 in 2017. After data cleaning, this study contains 1,679 respondents. The variables used in this study are shown in Table 1.

Based on the 3-day travel diary of MPN, the descriptive results indicate an increased reliance on car travel during the pandemic but also show a gradual shift towards active mobility in the latter years. Public transport, both in frequency and distance, remains below pre-pandemic levels, signaling the long-term impacts of the pandemic on public transport recovery. These shifts reflect the evolving patterns of mode choice.

The conceptual framework guiding this study is illustrated in Figure 1. The framework depicts the dynamic relationships among WFH hours, mode preference, commute distance, and car use frequency, which are key variables representing individual travel behavior and work-related patterns. The framework considers these variables to be mutually influencing over time, reflecting how changes in one variable may induce changes in others and capturing bidirectional effects over time.

To capture the dynamic relationships between WFH, commute distance, mode preference, and evolving mode choice, this study applies the random intercept cross-lagged panel model (RI-CLPM). RI-CLPM, an advanced variant of the traditional cross-lagged panel model (CLPM), addresses the limitations of between-person confounding by incorporating random intercepts, which capture stable, person-specific traits and remove them from the within-person relationships over time (Hamaker et al., 2015). The RI-CLPM is an advanced longitudinal modeling technique that allows for the exploration of reciprocal relationships between variables over multiple time points while accounting for stable between-person differences. The RI-CLPM captures both autoregressive effects, which represent the stability of each variable over time, and cross-lagged effects, which represent the directional influences between different variables across different waves.

Table 1. Variable definitions

Variables	Definitions
Key factors	
Working from home hour	Working from home hours in the recent week
Commute distance	Home-work distance
Mode preference	Preferred car for commuting trips or not
Car use	Car use frequency in three-day diary
Socio-demographics	
Gender	0: male 1: female
Age	2019 as the reference year 1: 18-29 years old 2: 31-59 years old 3: 60 years old and older
Education level	Highest education level in 2019 1: primary school or below 2: junior school 3: high school 4: bachelor's degree 5: master's degree or above
Built environment attributes	
Urbanity *	Urbanity level
Density *	Population density of the residential neighborhood
Diversity *	Land use diversity of the residential neighborhood
Distance to the nearest city center (km) *	Distance from home to the nearest city center
Distance to the nearest intercity station (km) *	Distance from home to the nearest train station
Distance to the nearest train station (km) *	Distance from home to the nearest intercity junction
Distance to the nearest bus stop (km) *	Distance from home to the nearest bus stop
Retails density	Retail density of the residential neighborhood
Intersection density	Intersection density of the residential neighborhood
Selected life events	
Life events	The occurrence of new job, stopped working, moving home, and childbirth from 2017 to 2022
Life events, t1-t3	The occurrence of new job, stopped working, moving home, and childbirth from 2017 to 2019
Life events, t4-t6	The occurrence of new job, stopped working, moving home, and childbirth from 2019 to 2022

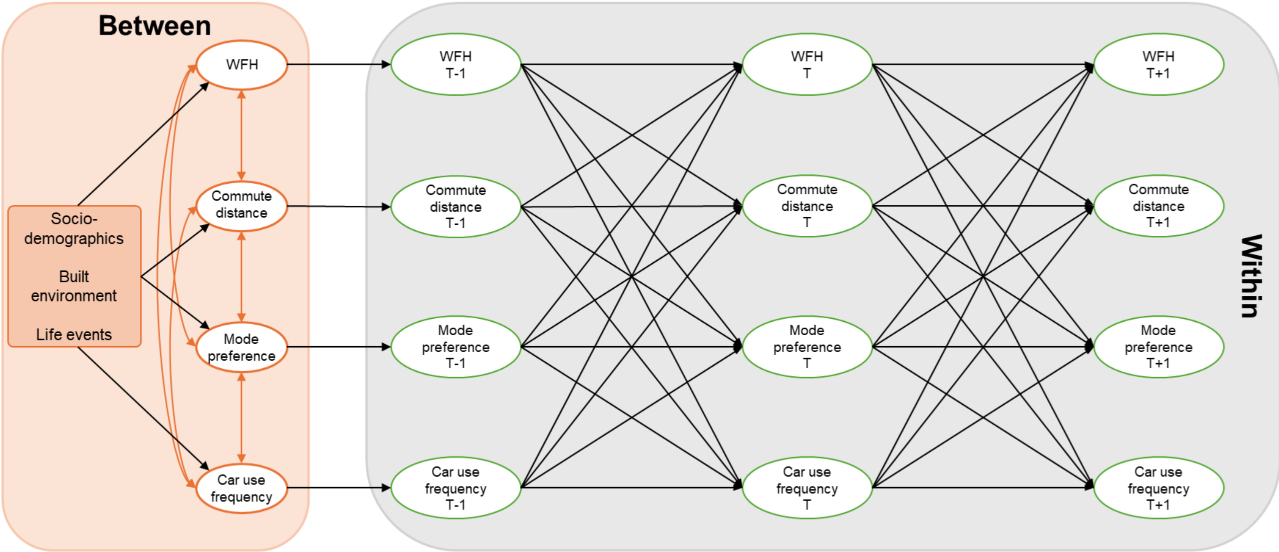

Figure 1. Conceptual framework

The RI-CLPM was estimated in Mplus with robust maximum likelihood estimation (MLR), which can deal with non-normality and missing data. The time reference points in this study are defined as follows: t1 = 2017, t2 = 2018, t3 = 2019, t4 = 2020, t5 = 2021, and t6 = 2022.

3. RESULTS

The model fit is assessed using multiple goodness-of-fit indices: chi-square/degrees of freedom (χ^2/df) = 1.628, comparative fit index (CFI) = 0.974, Tucker-Lewis index (TLI) = 0.963, root mean square error of approximation (RMSEA) = 0.019, and standardized root mean square residual (SRMR) = 0.018. All these indicate an acceptable model fit. The results are discussed as follows.

3.1. Autoregressive and cross-lagged effects

Autoregressive effects refer to the influence of a variable on itself over time. The autoregressive effects show that WFH exhibits strong temporal stability. The coefficient for WFH from t1 to t2 is 0.161 ($p = 0.048$), and the stability increases toward later waves, peaking at t5 to t6 with a coefficient of 0.377 ($p < 0.001$). Commute distance exhibits weaker autoregressive effects. Significant stability is observed in later waves, such as between t4 and t5 ($\beta = 0.291$, $p = 0.033$) and t5 and t6 ($\beta = 0.305$, $p = 0.006$). In contrast, several transitions, such as t2 to t3 and t4 to t5, are not significant, indicating fluctuations in commute behavior during certain periods. Car preference shows a mixed pattern. While the initial transition from t1 to t2 is highly significant ($\beta = 0.339$, $p < 0.001$), several waves show no significant autoregressive effects (e.g., t2 to t3, $p = 0.410$). A reversal is observed at t3 to t4 with a negative autoregressive effect ($\beta = -0.121$, $p = 0.035$), followed by a recovery between t5 and t6 ($\beta = 0.389$, p <

0.001), suggesting fluctuating mode preference, potentially linked to COVID-19. Finally, car use frequency exhibits significant autoregressive effects since t3 (t3 to t4: β = 0.102, p = 0.014; t4 to t5: β = 0.152, p = 0.015, t5 to t6: β = 0.189, p = 0.001).

Cross-lagged effects, are the influence of one variable on another variable across time. WFH only significantly influences car use between t4 to t5 (β = -0.117, p = 0.038). WFH has a positive impact on commute distance between t4 and t5 (β = 0.154, p = 0.086). WFH is significantly related to car preference at several points (t1 to t2: β = -0.078, p = 0.047; t4 to t5: β = -0.115, p = 0.043). Commute distance significantly predicts WFH at several points, but in the early wave, commute distance is negatively related to WFH (t2 to t3: β = -0.090, p = 0.020). During the pandemic period, commute distance is positively associated with WFH (t3 to t4: β = 0.153, p = 0.006; t4 to t5: β = 0.178, p = 0.001), indicating that longer commute distances are associated with WFH hours. There is also a significant predictive relationship between commute distance and mode preference at t1 to t2 (β = 0.111, p = 0.043), t3 to t4 (β = 0.126, p = 0.013), and t4 to t5 (β = 0.108, p = 0.005). This suggests that individuals with longer commutes tend to exhibit a stronger preference for cars over time. There are significant effects mode preference on commute distance at t1 to t2 (β = 0.075, p = 0.046), t2 to t3 (β = 0.121, p = 0.099), and t4 to t5 (β = 0.131, p = 0.016). Mode preference significantly predicts increased car use at t1 to t3 (β = 0.127, p = 0.001), reinforcing the notion that stronger car preferences lead to higher car use in subsequent periods. Car use frequency at t4 negatively affects WFH hours at t5 (β = -0.076, p = 0.058). Car use at T1 significantly positively predicts mode preference at T2 (β = 0.056, p = 0.079). Reversed effects show at t3 to t4 (β = -0.078, p = 0.056), after the happening of COVID-19.

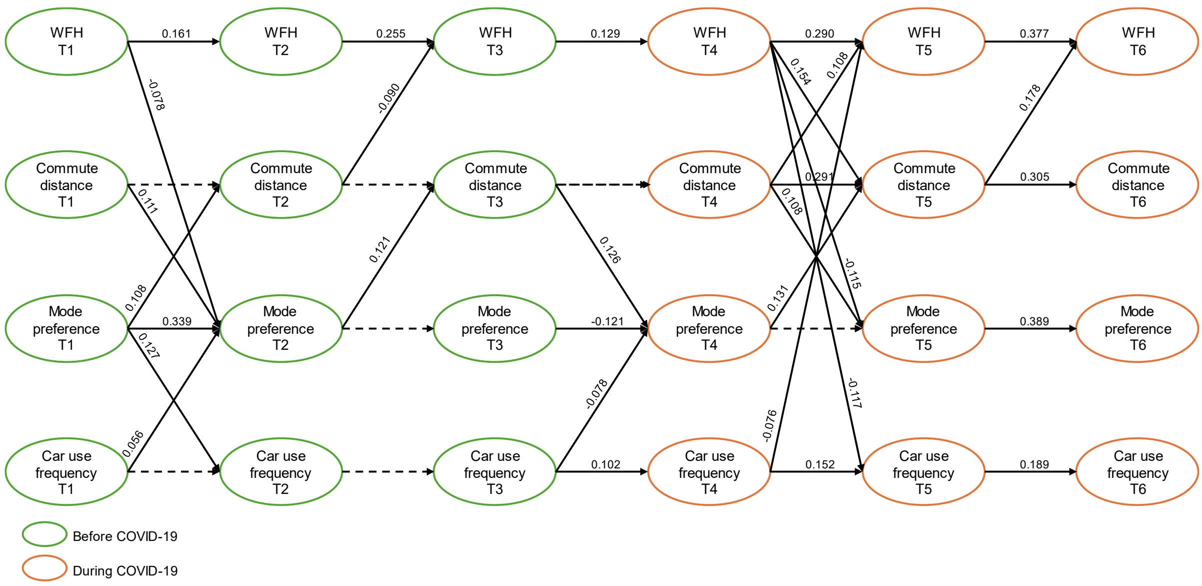

Figure 2. Reuslts of autoregressive and cross-lagged effects

3.2. Between-individual correlations

The results of the between-individual level correlations capture how stable individual differences influence the observed relationships between these variables over the two periods (pre- and post-

COVID-19). Before COVID-19, the correlations indicate that WFH is significantly related to car use frequency ($\beta = 0.093$, $p = 0.029$), mode preference ($\beta = 0.174$, $p = 0.001$), and commute distance ($\beta = 0.533$, $p < 0.001$). Mode preference also shows a significant positive association with car use ($\beta = 0.124$, $p = 0.001$), and commute distance is significantly associated with car use ($\beta = 0.283$, $p < 0.001$).

During the pandemic, the between-individual correlations generally weaken. The association between mode preference and car use remains highly significant ($\beta = 0.520$, $p < 0.001$), as does the relationship between mode preference and commute distance ($\beta = 0.259$, $p < 0.001$), indicating that stable individual preferences continue to influence these aspects of travel behavior in the COVID-19 period.

3.3. Effects of socio-demographics, built environment, and life events pre- and during COVID-19

Education has the strongest positive effect on WFH (β=0.314, p<0.001), while gender has a marginal negative association (β=-0.047, p=0.093). Among built environment factors, distance to the nearest train station (β=0.066, p=0.052) slightly increase WFH, whereas retail density (β=-0.062, p=0.024) reduce it. Childbirth (β=-0.067, p=0.080) and stopped working before the pandemic (β=-0.105, p=0.017) also negatively influence WFH. Commute distance is lower for women (β=-0.212, p<0.001) and older individuals (β=-0.285, p<0.001) but higher among the higher educated (β=0.112, p<0.001). Urban residents has shorter commutes (β=0.072, p=0.016). Starting a new job (β=0.117, p=0.031) or stopping working (β=0.128, p=0.014) increase commute distances, and stopping working before the pandemic (β=-0.188, p<0.001) has a negative effect. Car preference is shaped by gender (β=-0.135, p<0.001), age (β=-0.161, p<0.001), distance to train station(β=0.066, p=0.041) and bus stops (β=0.056, p=0.027). Relocation (β=-0.098, p=0.050) and stopped working (β=-0.083, p=0.059) marginally reduce preference, and childbirth and new jobs increase it. Car use frequency is higher in less urban areas (β=0.105, p=0.008) and with greater distance from bus stops (β=0.061, p=0.024), but lower in denser or retail-rich areas (β=-0.079, p=0.041; β=-0.064, p=0.002). Childbirth shows a marginal increase (β=0.077, p=0.063).

During the pandemic, women (β=-0.158, p<0.001) and young people (β=-0.151, p<0.001) has lower WFH hours, whereas higher education (β=0.298, p<0.001) has diverse effects. Distance to the city center (β=-0.122, p=0.002) also negatively affect WFH. Individuals who change jobs before (β=0.159, p=0.023) or during (β=0.093, p=0.086) the pandemic, as well as those who move home (pre-pandemic: β=0.489, p=0.072; during: β=0.297, p=0.089), are more likely to WFH. Commute distance is shorter for women (β=-0.256, p<0.001) and older adults (β=-0.364, p<0.001), yet longer among the highly educated (β=0.111, p<0.001). Mode preference is shaped by gender (β=-0.126, p<0.001), age (β=-0.186, p<0.001), urbanity (β=0.114, p=0.001), distance to bus stops (β=0.045, p=0.087), and retail density (β=-0.046, p=0.005). Childbirth before COVID-19 (β=0.138, p=0.017) increase car preference. Car use frequency is higher among higher educated individuals (β=0.061, p=0.041) and those in less urban areas (β=0.134, p=0.002). Neighborhood density (β=-0.090, p=0.019) and retail density (β=-0.054, p=0.010) reduce car use. Childbirth generally increase car use (β=0.168, p=0.023) but reduce it during the pandemic (β=-0.074, p=0.046).

Table 2. Effects of socio-demographics, built environment, and life events pre- and during-COVID-19

Variables	WFH		Commute distance	
	Pre-COVID	**During-COVID**	**Pre-COVID**	**During-COVID**
Gender	-0.047*	-0.158***	-0.212***	-0.256***
Age	-0.001	-0.151***	-0.285***	-0.364***
Education	0.314***	0.298***	0.112***	0.111***
Urbanity	0.040	-0.034	0.072**	0.032
Density	0.092*	0.017	-0.008	-0.049
Diversity	0.015	0.000	0.002	-0.008
Distance to city center	0.005	-0.122***	0.035	0.048
Distance to the nearest IC junction	-0.043	0.069*	-0.033	-0.047
Distance to the nearest train station	0.066*	0.024	-0.002	0.015
Distance to the nearest bus stop	0.014	0.017	-0.003	0.008
Retails density	-0.062**	-0.008	0.027	0.001
Intersection density	-0.009	0.023	0.033	0.038
New job	0.034	-0.081	0.117**	0.088
Stopped work	0.067	-0.129	0.128**	-0.057
Moving	-0.035	-0.435	-0.022	-0.081
Childbirth	-0.067*	-0.009	-0.004	-0.072
New job, t1-t3	-0.033	0.159**	-0.020	0.034
Stopped work, t1-t3	-0.105**	-0.025	-0.188***	-0.052
Moving, t1-t3	0.066	0.489*	0.040	0.120
Childbirth, t1-t3	0.037	-0.015	-0.016	0.055
New job, t4-t6		0.093*		-0.019
Stopped work, t4-t6		0.020		0.022
Moving, t4-t6		0.297*		0.058
Childbirth, t4-t6		-0.015		0.048
	Mode preference		**Car use**	
Gender	-0.135***	-0.126***	-0.052*	-0.050*
Age	-0.161***	-0.186***	0.022	-0.023
Education	0.005	-0.017	0.042	0.061**
Urbanity	0.132***	0.114***	0.105***	0.134***
Density	-0.060	-0.057	-0.079**	-0.090**
Diversity	-0.002	0.022	0.007	-0.028
Distance to city center	-0.012	-0.020	-0.019	0.075
Distance to the nearest IC junction	0.007	0.000	-0.038	-0.107*
Distance to the nearest train station	0.066**	0.043	0.000	0.009
Distance to the nearest bus stop	0.056**	0.045*	0.061**	0.011
Retails density	-0.026	-0.046***	-0.064***	-0.054**
Intersection density	0.052	0.044	-0.058	-0.023
New job	0.078*	0.080	0.072	0.097
Stopped work	0.032	0.055	-0.011	0.055
Moving	-0.098*	-0.170	-0.065	-0.112
Childbirth	-0.038	-0.103	0.077*	0.168**
New job, t1-t3	-0.011	-0.018	-0.037	-0.052
Stopped work, t1-t3	-0.083*	-0.078	-0.020	-0.051
Moving, t1-t3	0.044	0.116	0.034	0.093
Childbirth, t1-t3	0.094**	0.138**	0.016	-0.032
New job, t4-t6		-0.003		-0.040
Stopped work, t4-t6		0.006		-0.068
Moving, t4-t6		0.063		0.044
Childbirth, t4-t6		0.053		-0.074**

***: p-value < 0.01, **: p-value < 0.05, *:p-value < 0.1

4. CONCLUSIONS

This study offers a longitudinal analysis of dynamic relationships between WFH hours, commute distance, mode preference, and car use over a six-year period in the Netherlands. Applying RI-CLPM to decompose stable between-person differences from within-person changes over time, which allows for a deeper understanding of how different factors evolve and interact longitudinally. With the identification of autoregressive and cross-lagged effects, this study provides insights into the stability of evolving mode choice and the causal relationships between key factors over time.

Key findings indicate that increased WFH reduced car use frequency during COVID-19, underscoring WFH's potential to mitigate commuting by car. Meanwhile, longer commuting distance is positively linked to WFH adoption, as individuals want to avoid extended travel. Mode preference also shows a robust relationship with car use, highlighting habit-driven behavior. Socio-demographic factors, particularly gender, age, and education, proved significant, with older individuals, women, and those holding higher degrees more incline to reduce driving or adopt WFH. Built environment features, such as distance to public transport, influence car reliance, while life events (e.g., new jobs, childbirth, relocation) trigger shifts in travel behavior.

These findings inform policies aimed at reducing CO_2 emissions through targeted interventions. Although emerging mobility technologies contribute to decarbonization, this study highlights the importance of leveraging modal shifts and adapting infrastructure to encourage sustainable modes. The pandemic has served as a natural experiment, which demonstrates both the potential for rapid behavioral change and the persistence of habits and constraints. Encouraging WFH, improving public transportation travel, and supporting active travel modes can work together to advance a climate-neutral future for transportation, and ensure that policies meet both immediate needs and long-term sustainability goals.

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